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Three Essays on Credit Derivatives and Liquidity

Autor:
Armen Arakelyan

Director/es:
José Sebastián Penalva Zuasti

Departamento de Economía de la Empresa

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Three Essays on Credit Derivatives and Liquidity

Abstract

This thesis consists of three empirical essays on pricing credit derivatives and the impact of liquidity on the prices of credit derivatives. In essay one, I investigate empirically the pricing of Collateralized Debt Obligations (CDO) within the framework of copula models. In essay two I analyze the impact of illiquidity on Credit Default Swap (CDS) spreads on an individual level. In essay three I analyze the effect of market wide illiquidity on portfolio CDS spreads on an aggregate level. Overall, I contribute to the existing literature by proving evidence on the importance of liquidity on CDS spreads on both individual and aggregate level.

Esta tesis consiste de tres ensayos empíricos sobre la valoración de derivados de crédito y sobre el efecto de la iliquidez sobre los precios de estos derivados. En el primer ensayo, se analiza empiricamente la valoración de obligaciones de deuda colateralizada (CDO) utilizando funciones de cópulas. En el segundo ensayo se analiza el impacto de la falta de liquidez sobre los Credit Default Swap (CDS) a nivel individual. En el tercer ensayo, se analiza el impacto de iliquidez agregada sobre los spreads de carteras de CDS agregadas. En general, esta tesis contribuye a la literatura existente, enfatizando la importancia de la liquidez en los spreads de CDS, tanto a nivel individual como agregado.

Contents

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Introducción

El surgimiento de los mercados de derivados de crédito es relativamente un fenómeno nuevo. Dos décadas han pasado desde la creación de los primeros derivados de crédito por parte de JP Morgan en 1995. Sin embargo, en este corto período de tiempo los mercados de derivados de crédito han tenido un crecimiento sin precedentes tanto en términos de su tamaño como en la variedad de instrumentos que se crearon. Para el segundo semestre de 2011 el valor nominal de los contratos de derivados de crédito había superado los 32 millones de dólares USA (informe de BIS (2011)). Inicialmente, los primeros derivados de crédito fueron contratos de credit default swaps (CDS). Para satisfacer las necesidades crecientes de diversos grupos de inversores se crearon complejos instrumentos de derivados de crédito tales como obligaciones de deuda colateralizada (CDO), CDOs sintéticos, total return swaps (TRS), swaptions entre otros.

Sin embargo, ha habido costes altos asociados con el crecimiento de los mercados de derivados de crédito. Por ejemplo, hay una creencia general entre los académicos y políticos de que los mercados de derivados de crédito han provocado las recientes crisis financieras que se originaron en agosto de 2007 (véase, por ejemplo, Brunnermeier (2009)). Más concretamente, los derivados de crédito se han utilizado como instrumentos para negociar y transferir la deuda originada por las hipotecas subprime, por lo tanto, amplificando el efecto y la magnitud de la actual crisis financiera. La otra desventaja de los derivados de crédito antes del inicio de las crisis financieras es que esos instrumentos eran nuevos. Por lo tanto, también hubo una falta general de comprensión de como estos instrumentos funcionaban y se valoraban.

Ha habido también crecientes preocupaciones relacionadas particularmente con la liquidez de los derivados de crédito después del inicio de las crisis financieras. Esto se debe a las fricciones en los mercados de derivados de crédito, tales como las asimetrías de información (Acharya y Johnson (2007)) y los costes de búsqueda ((Duffie et al., (2007)). Los contratos de CDS se han creado en la demanda de instrumentos que puedan proporcionar información precisa sobre la solvencia de las compañías que estos contratos hacen referencia y por la posibilidad de la negociación de manera oportuna sobre el riesgo de crédito de sus empresas subyacentes. Por lo tanto, la presencia de fricciones en el mercado de derivados de crédito pueden "distorsionar" la verdadera medida de la solvencia de las empresas.

Estos factores enfatizan la importancia de comprender la manera en la que funcionan los derivados de crédito, la forma en que se valoran o en que se deberían valorarse estos instrumentos, y los factores que pueden influir a sus precios.

Esta tesis consiste de tres ensayos empíricos sobre la valoración de derivados de crédito y sobre el efecto de la iliquidez sobre los precios de estos derivados. En el primer ensayo, se analiza empiricamente la valoración de obligaciones de deuda colateralizada (CDO) utilizando funciones de cópulas. En el segundo ensayo se analiza el impacto de la falta de liquidez sobre los Credit Default Swap (CDS) a nivel individual. En el tercer ensayo, se analiza el impacto de iliquidez agregada sobre los spreads de carteras de CDS agregadas. En general, esta tesis contribuye a la literatura existente, enfatizando la importancia de la liquidez en los spreads de CDS, tanto a nivel individual como agregado. A continuación se ofrece una descripción general de los tres ensayos y las principales conclusions de ellos.

El primer ensayo se titula "Análisis VAR del modelo double t". En este ensayo se analiza empíricamente la valoración de obligaciones de deuda colateralizada (CDO) utilizando modelos de cópulas estadisticas. La relevancia de este estudio se justifica por el hecho de que la valoración de CDOs sigue siendo un campo abierto de investigación tanto en la literatura del riesgo de crédito como en la práctica. Esto se puede explicar en parte por la falta de éxito o "no-integridad" de los modelos utilizados para la valoración de tanto los CDOs como de productos de riesgo estructurado de crédito en general.

Los modelos de cópula fueron el primer paradigma que fueron aplicados para la valoración de CDOs. Dentro del enfoque de cópulas consideramos el modelo de double t cópula de Hull y White (2004) y la cópula gaussiana, siendo este último el estándar en el mercado para la valoración de los CDOs. Además de esto, llevamos a cabo un análisis dinámico (VAR) de los parámetros implicados del modelo de doble t copula. El objetivo del análisis VAR es examinar mejor los factores que puedan explican la dinámica de los parámetros del modelo double t copula. Por lo tanto, el análisis dinámico puede tener implicaciones para la cobertura de riesgo de la cartera de crédito en virtud de modelos de cópula.

En resumen, en este estudio empírico analizamos el modelo double t cópula de Hull y White (2004). Contribuimos a la literatura existente de dos maneras. En primer lugar, estimamos el modelo para los mercados europeos de derivados de crédito mediante el uso de los datos del mercado de los tramos de índice iTraxx Europe para el período de tiempo que va desde 27 de marzo de 2006 a 19 de septiembre de 2006. Obtenemos los spreads de los tramos del indice iTraxx Europe de Markit, y los spreads de CDS de las empresas en el índice iTraxx Europe de Datastream. En segundo lugar, llevamos a cabo un análisis dinámico de los parámetros del modelo de doble t cópula para examinar los factores que pueden explicar la dinámica de estos parámetros. El modelo de double t cópula reduce significativamente los errores de valoración de los tramos de CDOs en comparación con el modelo de Gaussian cópula, el estándar utilizado para la valoración de los CDOs. También encontramos que los parámetros óptimos de los grados de libertad del model double t copula varían de un día a otro. Los resultados de análisis VAR de los parámetros del model double t copula demuestran que el parámetro de la correlación implícita del modelo puede ser explicada por las principales variables financieras, tales como el índice de volatilidad VIX, los spreads de term y default. La raíz del error cuadrático medio (ECM), la medida de ajuste del modelo de double t copula a los spreads de tramos de CDOs, se ve afectado por el índice de volatilidad VIX y term spread. Las predicciones de fuera de la muestra de los parámetros del modelo con las variables exógenas empleadas se encuentran dentro del intervalo de confianza estimado al 95%.

El segundo ensayo se titula "Sobre los efectos de la iliquidez en los spreads de los CDS". En este ensayo se examina la "creencia generalizada" de los CDS, que establece que los spreads de CDS son una medida pura de riesgo de crédito de las empresas que estos CDSs hacen referencia. Sin embargo, ha habido una creciente evidencia empírica que sugiere que los spreads de los CDS no pueden ser completamente explicados por factores de riesgo de crédito relacionados con la empresa subyacente (Collin-Dufresne et al. (2001), Blanco et al. (2005), Tang y Yan (2008), Berndt et al. (2008)).

En este ensayo se evalúa la importancia de la liqudiez en los spreads de CDS cuando los inversores están negociando o cubriendo sus posiciones del riesgo de crédito bajo condiciones de altos riesgos financieros. Nuestra hipótesis es que la liquidez es un elemento importante en el CDS, debido a las fricciones en el mercado, tales como las asimetrías de información (Acharya y Johnson (2007)) y los costes de búsqueda ((Duffie et al., 2007)). Contamos con una serie de medidas para captar diferentes aspectos de la liquidez en los spreads de los CDS. Más concretamente, medimos la liquidez de CDS con los bid-ask spreads, el número de contribuyentes, la puntuación de liquidez de Fitch, medida de gamma iliquidez similar a la medida de la iliquidez de bonos de Bao, Pan y Wang (2011), y con la medida de iliqudiez de rendimiento-volumen similar a la medida de iliquidez de Amihud (2002) para las acciones.

Analizamos la relación entre la liquidez y CDS de dos maneras. En primer lugar, realizamos un análisis de datos de panel para estudiar la relación transversal entre las medidas de liquidez y los spreads CDS. En segundo lugar, hacemos el mismo análisis para cada uno de los componentes de CDS por separado, los cuales son la prima de riesgo y el componente de riesgo de incumplimiento. Para descomponer los spreads de CDS entre la prima de riesgo y componente de riesgo de incumplimiento aplicamos la metodología de Pan y Singleton (2008) y Longstaff et al. (2008). Nuestro análisis empírico se basa en una muestra amplia de 284 contratos de CDS de Markit. El período de tiempo que consideramos en nuestro análisis va desde enero de 2004 hasta abril de 2011, que también engloba el período de las crisis financieras recientes.

En resumen, nuestros resultados indican que los bid-ask spreads, gama medida de iliqudiez y la medida de iliquidez rendimiento-volumen son factores importantes para explicar la liquidez tanto de los CDS como de los constituyentes de los spreads de CDS, los cuales son la prima de riesgo y el componente de riesgo de incumplimiento. Además, similar a los resultados de Pan y Singleton (2008) encontramos que para los mercados corporativos de CDS una fracción importante de riesgo sistémico se valora a través de la prima de riesgo de CDS. Por último, encontramos que la utilidad del número de contribuyentes y la puntuación de liquidez de Fitch como medidas de liquidez es débil.

El tercer ensayo se titula "Liquidiez Agregada en los spreads de Credit Default Swaps". Como sugiere el título, este estudio analiza el efecto de las medidas de iliquidez agregadas en los mercados de CDS. La evidencia empírica sugiere claramente la presencia de un componente de liquidez en los CDS, independientemente de la calidad crediticia, vencimiento y tipo de subyacente (ver Buhler y Trapp (2008), de Jarrow (2010), y Bongaerts, Jong y Driessen (2011), entre otros). Sin embargo, la mayoría de los artículos analiza la importancia de la liquidez a nivel individual.

Este trabajo contribuye a la literatura analizando el efecto agregado de liquidez en los mercados de CDS. Estudiamos en profundidad el impacto de la iliquidez en los spreads de CDS a nivel agregado. En primer lugar, mostramos que, para una calificación crediticia y vencimiento dado, hay un movimiento comun en la liquidez de los contratos de CDS. A continuación, mostramos que la iliquidez agregada es un poderoso determinante de los spreads de los CDS. Hay una relación positiva y consistentemente significativa entre los spreads de CDS y los cambios de la iliqudiez agregada de mercado para todos los vencimientos y calificaciones crediticias. Por otra parte, esta relación es más fuerte durante los períodos de estrés. Por último, existe una relación monótona entre la sensibilidad a cambios en la liqudiez agregada de mercado y calificaciones crediticias, siendo esta sensibilidad más fuerte para los subyacentes de alto rendimiento. De hecho, el riesgo de liquidez agregada parece ser un factor más importante que el riesgo de crédito en el mercado de CDS. Esta conclusión es consistente con la importancia del fenómeno de flight-to-liquidity, dada la naturaleza variable en el tiempo del riesgo de liquidez en los spreads de CDS. Esto es especialmente importante en los plazos más cortos. Episodios de crisis a corto plazo reflejan flight-to-liquidity, pero no de flight-to-quality.

Introduction

The emergence of credit derivatives markets is relatively a new phenomenon. Two decades have passed since the creation of the first credit derivatives by JP Morgan in 1995. However, within this short period of time credit derivatives markets have had an unprecedented growth both in terms of their size and variety of instruments being traded. For the second half of 2011 the notional amount outstanding of credit derivative contracts surpasses 32 billion U.S. dollars (BIS (2011)). Initially, the first credit derivatives were credit default swap (CDS) contracts. To satisfy the increasing needs of various groups of investors, complex derivatives instruments, such as Collateralized Debt Obligation (CDO), Synthetic CDOs, Total Return Swaps (TRS), Credit Default Swaptions and others, have been created.

However, there have been high costs associated with the growth of credit derivatives markets. For instance, there is a general belief among academic scholars and policy makers that the credit derivatives markets have induced the recent financial crises that originated in August 2007 (see, for instance, Brunnermeier (2009)). More specifically, credit derivatives have been used as instruments to trade and transfer the debt originated by subprime mortgages, hence amplifying the effect and scale of the current financial crises. The other downside of credit derivatives before the start of the financial crises is that those instruments were new. Hence, there was also a general lack of understanding of the way these instruments work and were being priced.

There have been also growing concerns associated particularly with the liquidity of credit derivatives after the start of the financial crises. This is due to market frictions in credit derivatives markets, such as asymmetries of information (Acharya and Johnson (2007)) and costs of search (Duffie, Garleanu, and Pedersen (2007)). CDS contracts have been created in demand for instruments that can provide accurate information about the creditworthiness of companies that they reference and for the possibility of *timely* trading on the credit risk of their underlying companies. Hence, the presence of market frictions can "distort" the true measure of creditworthiness of companies.

These factors underline the importance of understanding the way credit derivatives work, the way they are/should be priced, and the factors that can influence their prices.

This thesis consists of three empirical essays on pricing credit derivatives and the impact of liquidity on the prices of credit derivatives. In essay one, I investigate empirically the pricing of Collateralized Debt Obligations (CDO) within the framework of copula models. In essay two I analyze the impact of illiquidity on Credit Default Swap (CDS) spreads on an individual level. In essay three I analyze the effect of market wide illiquidity on portfolio CDS spreads on an aggregate level. Overall, I contribute to the existing literature by proving evidence on the importance of liquidity on CDS spreads on both individual and aggregate level. Below I provide an overall description and the main findings of the three essays.

The first essay is titled "VAR Analysis of Double T Copula Model". In this essay I address the pricing of Collateralized Debt Obligations (CDOs) within the framework of copula models. The relevance of this study can be justified by the fact that CDO pricing still remains an open field of investigation both in the credit risk literature and in practice. This can be partially explained by the lack of success or "non-completeness" of the models used to price CDOs in particular or structured credit risk products in general. Copula models were the first paradigm to be applied to CDO pricing. Within the copula approach we consider the double t copula model of Hull and White (2004) and the Gaussian copula, the latter being the market standard for CDO pricing. Furthermore, we carry out a dynamic (VAR) analysis of the parameters implied from the double t copula model. The objective of the VAR analysis is to examine and have a closer look at the factors that drive the dynamics of the double t copula model parameters. Hence, the dynamic analysis can have implications for the portfolio credit risk hedging under copula models.

In short, in this study we empirically test the double t copula model of Hull and White (2004). We contribute to the existing literature in two ways. First, we estimate the model for the European credit derivative markets by using the market data on the iTraxx Europe index tranches for the time period ranging from March 27, 2006 to September 19, 2006. We obtain the data on tranche spreads from Markit, and the CDS spreads of the companies underlying the iTraxx Europe index from Datastream. Second, we carry out a dynamic analysis of the double t copula model implied parameters to examine the factors driving their dynamics. We find that the double t copula model significantly reduces the pricing errors compared to the Gaussian copula model, the standard used for CDO pricing. We also find that the optimal degrees of freedom parameters of the double t copula model change on a day-to-day basis. VAR analysis of the double t copula model parameters reveal that the implied correlation parameter of the model can be explained by major financial variables, such as the volatility index VIX, the term and default spreads. The root mean square error (rmse), the mispricing measure of the double t copula model, is affected by the volatility index VIX and the term spread. The out-of-sample predictions of the model parameters with the employed exogenous variables lie within the estimated 95% confidence interval.

The second essay is titled "On the effects of illiquidity in CDS spreads". In this essay I examine the "conventional wisdom" for CDSs, which states that CDS spreads are a pure price for credit risk of the companies that they reference. However, there has been a growing empirical evidence that suggests that CDS spreads may not be fully explained by credit risk factors related to the underlying company (Collin-Dufresne, Goldstein, and Martin (2001), Blanco, Brennan, and Marsh (2005), Tang and Yan (2008), Berndt, Douglas, Duffie, Ferguson, and Schranz (2008)).

In this essay we assesses the relevance of liquidity in default swap contracts when investors are hedging/trading under financially distressed conditions. We hypothesize that liquidity is an important element in CDS spreads because of the market frictions, such as asymmetries of information (Acharya and Johnson (2007) and search costs (Duffie et al. (2007)). We employ several measures to capture different aspects of liquidity in CDS spreads. More specifically, we proxy CDS liquidity with CDS bid-ask spreads, number of contributors, Fitch liquidity score, gamma measure of illiquidity similar to the bond illiquidity measure of Bao, Pan, and Wang (2011), and return-to-volume measure of illiquidity similar to the illiquidity measure of Amihud (2002) for stocks. We characterize the relationship between liquidity and default swap spreads in two ways. First, we perform a panel data analysis to study the cross-sectional relationship between our liquidity proxies and plain CDS spreads. Second, we do the same analysis for each of the CDS constituents separately, which are the distress risk premium and the default risk component. To decompose the CDS spreads into risk premium and default risk components we apply the methodology of Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2008).

Our empirical analysis is based on a comprehensive sample of 284 CDS contracts from Markit. The time period that we consider in our analysis spans from January 2004 to April 2011, covering the period of the recent financial crises. In short, our results indicate that the bid-ask spread, the asset's gamma and the return-to-volume measure are important factors in explaining liquidity of both CDS spreads and the constituents of CDS spreads, i.e. the risk premium and the default risk component. Additionally, similar to Pan and Singleton (2008) we find that an important fraction of systematic risk is being priced via the distress premium in corporate CDS markets. Finally, we find that the usefulness of the number of contributors and Fitch liquidity score as measures of liquidity is weak.

The third essay is titled "Market-Wide Lliquidity in Credit Default Swap Spreads". As the title suggests, this study analyzes market-wide liquidity in the CDS market. The empirical evidence clearly supports the presence of a liquidity component of CDS spreads independently of credit quality, maturity and type of underlying (see Buhler and Trapp (2009), Jarrow (2011), and Bongaerts, Jong, and Driessen (2011), among others). However, most papers analyze the importance of liquidity at the individual level.

This paper contributes to the literature by analyzing market-wide liquidity in the CDS market. We study thoroughly the impact of illiquidity on CDS spreads on an aggregate level. We first show that, for a given maturity and credit rating, there is a strong commonality in the liquidity of CDS contracts. Then, we show that market-wide illiquidity is a powerful determinant of CDS spreads. There is a consistently positive and significant relation between CDS spreads and market-wide illiquidity changes across all maturities and credit qualities. Moreover, this relation is stronger during stress periods. Finally, there is a monotonic relationship between sensitivity to market-wide changes of liquidity and credit ratings, being this sensitivity stronger for high yield underlyings. Indeed, aggregate illiquidity risk seems to be a more important factor than credit risk in the CDS market. This conclusion is also supported by a significant flight-to-liquidity given the time-varying nature of liquidity risk embedded in CDS spreads. This is particularly important at the shortest maturities. Crisis episodes reflect short-term flight-to-liquidity but not flight-to-credit quality.

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Chapter 1

VAR Analysis of Double T Copula Model

Abstract

In this paper we empirically test the double t copula model of Hull and White (2004). We contribute to the existing literature in two ways. First, we estimate the model for the European credit derivative markets by using the market data on the iTraxx Europe index tranches for the time period ranging from March 27, 2006 to September 19, 2006. Second, we carry out dynamic analysis of the double t copula model implied parameters to examine the factors driving their dynamics. We find that the double t copula model significantly reduces the pricing errors compared to the Gaussian copula model, the standard used for CDO pricing. We also find that there is a change in the optimal degrees of freedom parameters of double t copula model on a day-to-day basis. VAR analysis of the double t copula model parameters reveals that the implied correlation parameter of the model can be explained by major financial variables, such as the volatility index VIX, the term and default spreads. The root mean square error(rmse), the mispricing measure of the double t copula model, is affected by the volatility index VIX and the term spreads. The out-of-sample predictions of the model parameters with the employed exogenous variables lie within the estimated 95% confidence interval.

1 Introduction

CDO pricing still remains an open field of investigation both in the credit risk literature and in practice. This can be partially explained by the lack of success or “non-completeness" of the models used to price CDOs in particular or structured credit risk products in general. By looking at the mispricing of different approaches used to price CDOs we hope to help improve existing models, and hopefully improve credit risk management and hedging.

In this paper we focus on the copula approach, which was the first paradigm to be applied to CDO pricing. Within the copula approach we consider the double t copula model of Hull and White (2004) and the Gaussian copula, the latter being the market standard for CDO pricing. We have chosen the double t copula model for our analysis based on the empirical performance of this model relative to other copula approaches. For instance, for August 4, 2004 Hull and White (2004) found that the double t copula model with even degrees of freedom provides the best fit to the iTraxx Europe and CDX index tranche spreads. Burtschell et al. (2009) find the same result based on the iTraxx European tranche data for February 8, 2005. Other papers using the double t copula model and finding similar results are Kalemanova et al. (2007) and Mortensen (2005). However, all these studies base their analysis on a cross sectional data for a single day (non-intra day).

Wang et al. (2009) estimate the double t copula by using market data for 248 days for the North American credit derivatives market. One of the contributions of our paper is that we test the double t copula model for the European credit derivatives market. In doing so we use a sample size of 114 days. Like Wang et al. (2009), we consider a more general case where the two degrees of freedom parameters of the double t copula model are allowed to be non-integer numbers as opposed to the conventional model specification, in which the degrees of freedom parameters are restricted to be whole numbers.[1] Note that in the double t copula model the first degrees of freedom parameter represents the state of the common factor affecting all the names in a credit portfolio, whereas the second degrees of freedom parameter characterizes the idiosyncratic state of each name. The other contribution of our paper is that we carry out a dynamic (VAR) analysis of the parameters implied from the double t copula model. The objective of the VAR analysis is to examine and have a closer look at the factors that drive the dynamics of the double t copula model parameters. Hence, the dynamic analysis can have implications for the portfolio credit risk hedging under copula models.

[1]By allowing the degrees of freedom parameters to be time varying, we aim to capture extra variation in the time series of the degrees of freedom parameters, which can be critical for determining the factors driving their dynamics.

To test the model, we consider the data on the iTraxx Europe credit index and its tranches ranging from March 27, 2006 to September 19, 2006. The index and tranche maturities are 5 years, which is the most typical maturity for this type of products. We also compare the results with those obtained for the one factor Gaussian copula that serves as benchmark. We find that on average the double t copula reduces pricing errors by more than four times compared to the one factor Gaussian copula model. As for the degrees of freedom parameters of the double t copula model, we find that two degrees of freedom parameters of the double t copula model estimates from market data vary on a day-to-day basis and are different one from the other. This is in contrast to the methodology and results of Wang et al. (2009) where they estimate the double t copula model with one time varying degrees of freedom parameter equal for both factors.

In the literature of CDO pricing, some authors (see, for instance, Hull and White (2004), Burtschell et al. (2009)) have considered the double t copula model with both degrees of freedom parameters equal to 4. We test for the time invariance in the parameters using mean tests for the degrees of freedom parameters of the double t copula model. First, the hypothesis that the means of two degrees of freedom parameters are the same is rejected at the 5 percent level against the alternative that they are different. Second, we fail to reject the hypothesis that the first degrees of freedom parameter is equal to four, but we reject the hypothesis that the second degrees of freedom parameter is four.

Finally, we study the time series behaviour of the implied model parameters and the pricing errors of the double t copula model. To do this, we conduct a VAR analysis of the implied correlation of the double t copula model, two degrees of freedom parameters of the model as well as the root mean square error (RMSE). We also control for a number of variables representing major volatility, treasury and corporate bond markets. Those are the volatility index VIX, treasury term spread defined as the difference between the 10 year constant maturity treasury bond yields and 1 year constant maturity treasury bill yields, and the default spread of Moody's, defined as the difference between Moody's Aaa and Baa corporate bond yields.

The time series of the implied default correlation parameter of the double t copula model can be explained by all the considered exogenous variables.[2] The relationship between the implied correlation of the double t coupla model and the VIX index is positive and statistically significant. An increase in the VIX index

[2]Note, that in what follows the interpretation of the VAR results hold for the risk neutral parameters that are implied from the double t copula model. In particular, as we do not have historical measures of default time correlation, we cannot separate "objective" correlation under P measure from the "priced" correlation under Q measure. Hence, the interpretations are relevant for the market price or premium inherent in default time correlation.

might be interpreted as an increase in overall market uncertainty, which can also contribute to the increase in the default correlation among various companies. The negative sign of the term spread may indicate that increasing term spreads may reduce the riskiness of many companies as measures by the CDS spreads, hence may also decrease the default correlation among them. In corporate bond markets, the Moody's default spread is has a positive and a significant effect on the correlation. The intuition behind the positive sign is that growing default spreads can signal concerns about the creditworthiness of the companies, hence induce increases in the default correlation among them.

We find that model mispricing, measured by the root mean square error, can be explained by such macro factors as the volatility index VIX and the term spreads. The sign of the coefficient for the VIX is negative and statistically significant, whereas the sign of the coefficient of the term spread is positive and also statistically significant. The positive sign of the coefficient of the the VIX index indicates that the double t copula model captures better the tranche spreads of the iTraxx Europe index when there are volatile conditions expected over future time horizons. On the other side, the positive sign of the coefficient of the term spread suggests that the model captures worse the tranche spreads when good economic conditions are expected. Overall, these results seem to suggest that the double t copula model captures better the tranches of the iTraxx Europe index for expected bad times than for good times.

The explanatory power of the degrees of freedom parameters is at most at the 10 percent level, and the coefficients of the variables of those equations are difficult to interpret. The out-of-sample predictions for the model parameters show acceptable forecasting power.

The rest of the paper is organized as follows: Section 2 gives a literature review of the work that has been done in credit derivatives pricing. Section 3 describes the general approach to synthetic CDO tranche pricing. Section 4 present the theory of portfolio loss distribution function modelling and building within the factor copula framework. It also reviews one factor Gaussian and double t copula models, respectively. Section 5 describes the data. Section 6 reports the results from empirical analysis. Section 7 summarizes the results and concludes.

2 Literature Review

Due to its simplicity and tractability, the one factor Gaussian copula, introduced by Vasicek (1987), Vasicek (1991) and later formalized by Li (2000), has become the market standard for CDO pricing. However, the theoretical foundations of the model have been questioned. It performs poorly when one tries to replicate market prices for tranches of a CDO with a constant correlation parameter. Furthermore, the empirical correlation numbers, implied by the market tranche spreads of the same CDO assuming a Gaussian copula, are not constant and form a smile shape. The weaknesses of the model have been found to be the one factor correlation structure and the lack of tail dependence in the Gaussian copula.

To overcome some of the problems of the one factor Gaussian copula, a number of authors have proposed alternative parametrizations of the one factor copula. Hull and White (2004) extend the model by changing the distributional assumptions in factor copulas from normal to Student t. This gives rise to the so called double t copula model. Kalemanova et al. (2007) introduce another factor copula by considering the normal inverse Gaussian distribution for portfolio loss default modelling. Andersen and Sidenius (2005) extend the model by randomizing recovery rates and factor loadings. Another paper introducing a stochastic correlation structure in the portfolio loss default modelling is Burtschell et al. (2007). Other copulas have been proposed: Student t (Marshall and Naldi (2002), O'Kane and Schloegl (2002), Demarta and McNeil (2005), Clayton (Schonbutcher (2001), Rogge and Schonbutcher (2003), Marshall-Olkin (Marshall and Olkin (1976), Duffie and Singleton (1998)).[3] However, their performances have been marginally satisfactory. A good introduction and comparisons of the Gaussian, stochastic correlation Gaussian, Student t, double t, Clayton and Marshal-Olkin copula models can be found in Burtschell et al. (2009). Brunlid (2006) describes the generalized hyperbolic copulas, that are skewed, and include the normal inverse Gaussian, the variance gamma and the skewed Student t copulas.

Another line of research has looked into increasing the number of factors in the model. This approach has been considered, among others, by Hull and White (2004), Lucas et al. (2001), and Moreno et al. (2008). For a theoretical treatment of the pricing issues of the multi-factor copulas when the factors are Gaussian, see

[3]Note, that the double t and student t copulas are similar in that they both employ student t distribution. However, these are two different models as the double t copula model assumes that both the common and idiosyncratic factors of the model follow a student t distribution, whereas the Student t copula assumes that the weighted sum of the common and idiosyncratic factors is student t. As the sum of two student t random variables is not a student t random variable, those two specifications give rise to two different copula models.

Glasserman and Suchintabandid (2006), Iscoe and Kreinin (2007).

An important aspect of the factor copula models is the assumption of conditional independence. This assumption allows to significantly reduce the computational dimension of the problem, and to derive semi-analytical formulas for CDO portfolio loss distribution functions. Andersen and Sidenius (2003) use recursive methods to build up the portfolio loss function, while Hull and White (2004) apply a similar technique by considering the probability bucketing procedure in case recovery rates and credit principals in the underlying portfolio are different. Andersen and Sidenius (2005) also propose a technique for portfolio loss distribution evaluation when the notional amounts and the recovery rates of underlying portfolio names are pairwise different. Laurent and Gregory (2003) employ another technique which first evaluates the characteristic function of portfolio loss and then inverts it numerically to back out the portfolio loss function. A comparison of different methods to build up the portfolio loss distribution is done by Jackson et al. (2004).

In all empirical studies of copula models outlined above the time period is only one day. Wang et al. (2009) extend these results by considering a sample size of 248 days for North American credit derivatives market. They fit a one factor heavy tailed copula model to the data. More specifically, they test the double t copula model where the degrees of freedom parameters of the model are fractional. They also test another copula model where they consider the mixture distribution of t and Gaussian copula models. In our paper we also test the double t copula model with varying degrees of freedom parameters for a sizeable sample of days. By contrast, we test the model for European credit derivatives market. Then we go a step further, and do a dynamic (VAR) analysis of the double t copula model implied parameters.

Other approaches to CDO valuation have been proposed. The paper by Duffie and Garleanu (2001) is one of the first in the credit derivatives literature that applies the default intensity approach to CDO pricing. They model the default intensities of credit names in portfolio as affine jump processes, and derive closed form solutions for correlated default probabilities of portfolio names. This approach has been further extended and examined, among others, by Mortensen (2005), Feldhutter (2008) and Eckner (2009).

An alternative way to model CDO credit portfolios is to follow the top-down approach. Rather than modelling individual defaults, the distribution function of portfolio loss is modelled directly. Then, so called thinning techniques can be applied to derive individual credit dynamics. Papers following this approach are Longstaff and Rajan (2008), Giesecke and Goldberg (2009), Halperin and Tomecek (2009), Schonbutcher

(2006), Bielecki et al. (2008), to name a few.

3 Synthetic CDO Tranche Pricing Equation

In this section we cover the pricing of a synthetic CDO which is tailored by a pool of single name Credit Default Swap (CDS) contracts as opposed to a cash CDO where the underlying portfolio contains more traditional fixed-income securities. For a comprehensive description and understanding of CDS contracts and their market, see Merrill Lynch (2006a).

CDOs are used to reallocate the credit risk of a portfolio by parts. To this end, they are divided into several classes, called tranches. Each tranche is a bilateral contract with predefined maturity where the CDO tranche issuer (protection seller) agrees to pay to the CDO tranche buyer (protection buyer) all the losses that happen in the portfolio associated with that tranche until maturity. On the other side, the tranche holder compensates the tranche issuer for protection by making periodic payments proportional to the outstanding tranche notional up to tranche maturity.[4] The portfolio losses that the tranche covers in case of default is defined by the attachment / detachment points. For a general description of CDO structures, their types and applications see the handbook by Merrill Lynch (2006b).

In general terms, let's consider a CDO tranche with maturity T that provides protection against portfolio losses in the range of L_a and L_d ($0 \leq L_a < L_d \leq 1$), where L_a and L_d define attachment/detachment points, respectively. The tranche spread made by the protection buyer to the protection seller per annum is denoted by $S_{[L_a,L_d]}$. Additionally, let $t_1 < \ldots < t_J = T$ denote the tranche spread payment dates, and $t_0 < t_1$ the tranche valuation date.[5]

As we will see later, the protection and default payments require the evaluation of the expected tranche loss function, which we consider next. As tranche $[L_a, L_d]$ provides credit protection against portfolio losses $L(t)$ in pre-specified range of L_a and L_d, the tranche loss can be written as:

$$\mathscr{L}_{[L_a,L_b]}(t, L(t)) = \frac{1}{L_d - L_a}\left[(L(t) - L_a)^+ - (L(t) - L_d)^+\right] \tag{1}$$

[4] The outstanding notional of a tranche is the amount that is left from the initial tranche notional after having paid all the expected losses associated with the given tranche. The notional amount of a financial instrument is the nominal value that is being used to calculate payments made on that instrument.

[5] For many structured credit derivatives, traded in the OTC markets, the spread payment frequency is usually quarterly, i.e. $t_j - t_{j-1} \approx 1/4$.

For ease of exposition, let's assume the portfolio loss distribution function $F_{L(t)}(l)$ of the loss process $L(t)$ is continuous both in time and in loss amount. Then, the expected cumulative tranche loss over the $(0,t)$ time interval under risk neutral probability measure Q will be:

$$\begin{aligned} E_{[L_a,L_b]}(t) &\doteq E_Q\left\{\mathscr{L}_{[L_a,L_b]}(t,L(t))\right\} = \frac{1}{L_d - L_a}\left[\int_0^1 \left[(l-L_a)^+ - (l-L_d)^+\right] dF_{L(t)}(l)\right] \\ &= \frac{1}{L_d - L_a}\left[\int_{L_a}^1 (l-L_a)\, dF_{L(t)}(l) - \int_{L_b}^1 (l-L_b)\, dF_{L(t)}(l)\right] \end{aligned} \tag{2}$$

However, as it will become clear later in practice, the portfolio loss distribution function $F_{L(t)}(l)$ is discrete in loss amounts. Hence, for the expected tranche loss calculation it will suffice to calculate $Prob[L(t)=l]$, where l denotes the discrete value that the portfolio loss can take on. These values are a non-trivial function of the number of names in the portfolio, the nominal amounts and the recovery rates associated with all the names in the portfolio. Though it might not be immediately obvious, the expected tranche loss is a deterministic function of time.

To determine the breakeven spread of a single tranche CDO, the payments (also called legs) made by both protection buyer and protection seller should be defined. But first let $D(t)$ be the discount factor defined as $D(t) = \exp\left\{-\int_{t_0}^t r(s)\, ds\right\}$, where $r(t)$ is the risk free interest rate. For simplicity, we will assume $r(t)$ to be independent of portfolio loss process $L(t)$.

Then, the value of the Premium Leg is equal to an upfront payment plus the present value of all the spread payments made by the protection buyer to the protection seller.[6]

$$PL = U_{[L_a,L_d]} + E_Q\left\{\sum_{j=1}^{J} \Delta t_j S_{[L_a,L_d]} D(t_j)\left[1 - \mathscr{L}_{[L_a,L_b]}(t_j, L(t_j))\right]\right\} \tag{3}$$

$$= U_{[L_a,L_d]} + S_{[L_a,L_d]} \times \sum_{j=1}^{J} \Delta t_j D(t_j)\left[1 - E_{[L_a,L_b]}(t_j)\right] \tag{4}$$

where $U_{[L_a,L_d]}$ is the upfront payment made by the protection buyer to the protection seller at $t = t_0$. This upfront payment is mostly required for the so called equity tranche, that is, the one with zero attachment

[6] The Premium Leg also includes accrued payments at default. It means that if there has been a default at time τ^- proceed by a new default at time τ between two consecutive tranche spread payment dates t_{j-1} and t_j, i.e. $(\tau \in (t_{j-1}, t_j))$, then an accrued payment in the amount of $(\tau - t^-)S_{[L_a,L_d]} \times \left[\mathscr{L}_{[L_a,L_b]}(\tau, L(\tau)) - \mathscr{L}_{[L_a,L_b]}\left(t^-, L(t^-)\right)\right]$ should be made at default time τ, where $t^- \doteq \max(\tau^-, t_{j-1})$. For notational simplicity, we don't include them in the pricing formula, but take them into account in the numerical analysis.

point. For the equity tranche the spread payment $S_{[0,L_d]}$ is usually fixed. $\Delta t_j = t_j - t_{j-1}$ is the time period between two spread payment dates, measured in fractions of a year. As the spread payments are made for consecutive time periods, then $\Delta t_j S_{[L_a,L_d]}$ will be the effective spread adjusted for the time period $t_j - t_{j-1}$. Also note that $1 - E_{[L_a,L_b]}$ is the tranche outstanding notional, where the initial tranche principal is normalized to one.

The value of the Default Leg (Protection Leg) is equal to the expected value of the discounted random loss payments $d\mathscr{L}_{[L_a,L_b]}$ made by protection seller to the protection buyer at default. Hence,

$$DL = E_Q\left\{\int_{t_0}^{T} D(t)\, d\mathscr{L}_{[L_a,L_b]}(t, L(t))\right\} \tag{5}$$

where $d\mathscr{L}_{[L_a,L_b]}(t,L(t))$ is a shorthand for $\left[\partial \mathscr{L}_{[L_a,L_b]}(t,L(t))/\partial t\right] dt$

If we assume that default happens on the spread payment dates, then the Default Leg can be approximated by:

$$DL \approx E\left\{\sum_{j=1}^{J} D(t_j)\left[\mathscr{L}_{[L_a,L_b]}(t_j, L(t_j)) - \mathscr{L}_{[L_a,L_b]}(t_{j-1}, L(t_{j-1}))\right]\right\} \tag{6}$$

$$= \sum_{j=1}^{J} D(t_j)\left[E_{[L_a,L_b]}(t_j) - E_{[L_a,L_b]}(t_{j-1})\right] \tag{7}$$

The break-even spread $S_{[L_a,L_d]}$ for tranche $[L_a, L_d]$ is calculated by equating the value of the Default Leg to that of the Premium Leg.

$$S_{[L_a,L_d]} \approx \frac{\sum_{j=1}^{J} D(t_j)\left[E_{[L_a,L_b]}(t_j) - E_{[L_a,L_b]}(t_{j-1})\right]}{\sum_{j=1}^{J} \Delta t_j D(t_j)\left[1 - E_{[L_a,L_b]}(t_j)\right]} \tag{8}$$

As mentioned previously, an upfront payment is mostly required for the equity tranche, while its running spread $S_{[0,L_d]}$ is fixed. For the iTraxx Europe index, which we will describe later, the running spread of the equity tranches is fixed at the level of 500 basis points (bp). Hence, when there are upfront payments, i.e. when $S_{[L_a,L_d]}$ is fixed, equation $DL = PL$ should instead be solved for the optimal value of $U_{[L_a,L_d]}$.

4 Portfolio Default Modelling

Given the loss distribution function of a credit portfolio over any time horizon, the spread calculation of a tranche is straightforward. However, the evaluation of the portfolio loss distribution is per se challenging. One of the principal difficulties arises from the fact that default by one credit name in the portfolio may trigger default(s) of others. In other words, default processes of the credit names in the portfolio can be correlated. Introducing an appropriate correlation structure among portfolio credit default times constitutes one of the major challenges for CDO pricing. This section addresses the issues related to the correlated default modelling and portfolio loss distribution building within the so called copula approach.

Let the CDO portfolio be composed of n names with associated random default times $\tau_1, \tau_2, \ldots, \tau_n$ defined on the probability space $(\Omega, \mathscr{F}, Q)$. Additionally, let N_i denote the notional amount of name i, and $R_i(t) \in [0,1]$ the non-stochastic recovery rate associated with portfolio name i. We will assume that the individual risk neutral default probabilities $p_i(t) = Q(\tau_i \leq t), \forall i = 1, \ldots, n$ of all names are known or otherwise can be bootstrapped from the market CDS quotes. More specifically, in our numerical analysis we will use the following approximation of the individual risk neutral default probabilities of any name i:

$$p_i(t) = 1 - \exp\left\{-S_i^{cds}(T)/(1-R_i) \cdot t\right\}, \forall t \leq T$$

where $S_i^{cds}(T)$ is the CDS spread of name i with T years of maturity, and R_i is the expected recovery rate of name i in default.

The pro-rata loss amount generated by credit name i in default is: $l_i(t) = \delta_i(1 - R_i(t))$, where $\delta_i = N_i / \sum_{i=1}^{n} N_i$ is the weight of name i in the total CDO notional. Hence, the aggregate portfolio loss $L(t)$ at time t will be given by:

$$L(t) = \sum_{i=1}^{n} \delta_i (1 - R_i(t)) 1_{\tau_i \leq t} \tag{9}$$

where $1_{\tau_i \leq t}$ is the default indicator function of name i. It is equal to one if credit name i defaults by time t, and zero otherwise.

To calculate the portfolio loss density function $Prob(L(t) = l)$ one should be able to account for the correlation among the default indicator processes $1_{\tau_i \leq t}$ for any name i.

4.1 The Copula Approach

Copula functions are widely used to account for correlation among credit defaults. If we define $F_i(t) \doteq Q(\tau_i \leq t)$ to be the continuous marginal distribution function of random variable τ_i, and $F(t_1,\ldots,t_n) \doteq Q(\tau_1 \leq t_1,\ldots,\tau_n \leq t_n)$ the joint distribution function of τ_i's, then by Sklar's theorem Sklar (1973) there exists a copula function $C:[0,1]^n \to [0,1]$ such that $F(t_1,\ldots,t_n) = C(F_1(t_1),\ldots,F_n(t_n))$. In other words, copula functions serve to combine the marginal distributions into a multivariate one. An example of a copula that is widely used in the modelling of correlated defaults is the Gaussian one: $C^{(G)}(F_1(t_1),\ldots,F_n(t_n)) = \Phi_\Sigma\left[\Phi^{-1}(F_1(t_1)),\ldots,\Phi^{-1}(F_n(t_n))\right]$, where Φ_Σ is the multivariate normal distribution function with correlation matrix Σ. For a detailed presentation of copula functions and their applications, see Cherubini et al. (2004), Galiani (2003), Embrechts et al. (2001), Schmidt (2006).

It should be noted that the conventional copula approach for CDO pricing is based on correlated default time simulations. One of the main reasons is that the evaluation of the joint distribution function F at a given set of data points $(t_1,\ldots,t_n)$ involves an n-dimensional integration, which can be quite complicated if not impossible. A Monte-Carlo algorithm to simulate correlated default times within the Gaussian copula framework is described by Li (2000). Briefly, if we generate a series of random variables $V_i = \Phi^{-1}(F_i(\tau_i))$, $i = 1,2,\ldots,n$ from the n-dimensional normal distribution by using the Cholesky decomposition of the correlation matrix Σ, the correlated default times can be obtained by $\tau_i = F_i^{-1}(\Phi(V_i))$. Once the correlated default times are simulated, then it becomes straightforward to calculate the contingent tranche payments, hence the optimal tranche spreads of the CDO.

This approach is quite general and easily implemented. However, for an accurate estimation of the tranche spreads of a CDO a large number of simulations is needed, as the Monte-Carlo simulations are slow to converge.

4.2 The One Factor Copula Approach

The one factor copula is another approach that is being used to define the co-dependence structure of times to default. Unlike the conventional copula approach, it allows to get semi-analytical expressions for the portfolio loss density function, and thus, also for the CDO tranche spreads.

Within the factor copula approach, one assumes that the credit name i's time to default τ_i is related to another random variable $V_i(t)$, such that i-th issuer defaults whenever $V_i(t)$ goes below a non-stochastic threshold level $B_i(t)$:

$$1_{\tau_i \leq t} \quad \equiv \quad 1_{V_i(t) \leq B_i(t)}, \text{ for } i = 1, \ldots, n \tag{10}$$

In some papers, $V_i(t)$ is conveniently interpreted as company i's asset return process, and $B_i(t)$ the company's liquidation value. In this general framework, we will simply treat $V_i(t)$'s as random latent variables.

Let the distribution function $F_{V_i(t)}(v)$ of random variable $V_i(t)$ be continuous and invertible. Then the equality $Q(\tau_i \leq t) = Q(V_i(t) \leq B_i(t))$ will follow if $B_i(t) = F^{-1}_{V_i(t)}(p_i(t))$. Recall, that $p_i(t)$'s are the bootstrapped default probabilities of the underlying portfolio names, which we calculate using the following approximation:

$$p_i(t) \quad = \quad 1 - \exp\left\{-S_i^{cds}(T)/(1-R_i)\cdot t\right\}, \forall t \leq T, i = 1, \ldots, n \tag{11}$$

To generate the one factor correlation structure among the underlying portfolio default times, the latent variable $V_i(t)$ is further decomposed as:

$$V_i(t) \quad = \quad \rho_i X(t) + \sqrt{1-\rho_i^2}\mathscr{E}_i(t), \text{ for } i = 1, \ldots, n \tag{12}$$

where the random variables $X(t)$ and $\mathscr{E}_i(t)$'s are mutually independent and are assumed to have zero mean and unit variance.[7] $X(t)$ is referred to as the common factor affecting all credit names in the portfolio, and $\mathscr{E}_i(t)$ is the idiosyncratic component specific to credit name i.

One of the most important features of the factor copula approach, outlined in equations (10) and (12), is that the default times of the underlying portfolio names become independent conditional on the common factor X:

$$F(t_1, \ldots, t_n \mid X(t)) \doteq Q(\tau_1 \leq t_1, \ldots, \tau_n \leq t_n \mid X(t)) = \prod_{i=1}^{n} Q(\tau_1 \leq t_1 \mid X(t))$$

The conditional independence result considerably facilitates the calculation of the portfolio loss distribution function. To see this, let $p_i(t|x) \doteq Q(\tau_i \leq t | X(t) = x)$. Then, the conditional default probability of name

[7]Even if we assume that $X(t)$ and $\mathscr{E}_i(t)$ are not zero mean and unit variance random variables, the results that follow will not change. Note also, that with the given assumptions for X and $\mathscr{E}_i$'s, random variable V_i will also have a zero mean and unit variance.

i can be calculated as:

$$
\begin{aligned}
p_i(t|x) &\doteq Q(\tau_i \le t|X(t)=x) = Q(V_i(t) \le B_i(t)|X(t)=x) \\
&= Q(\rho_i X(t) + \sqrt{1-\rho_i^2} E_i(t) \le B_i(t)|X(t)=x) = F_{\mathscr{E}_i(t)}\left(\frac{B_i(t)-\rho_i x}{\sqrt{1-\rho_i^2}}\right)
\end{aligned} \tag{13}
$$

where $F_{\mathscr{E}_i(t)}$ is the distribution function of the idiosyncratic factor $\mathscr{E}_i(t)$, and $B_i(t) = F^{-1}_{V_i(t)}(p_i(t))$. For simplicity, let's suppose the underlying CDO portfolio is homogeneous, i.e. the initial notional amounts, recovery rates, risk neutral default probabilities and factor loadings are the same for all portfolio names. Then,

$$
p_i(t|x) = p(t|x) = F_{\mathscr{E}(t)}\left(\frac{B(t)-\rho\, x}{\sqrt{1-\rho^2}}\right), \forall i = 1,\ldots,n
$$

and the portfolio loss takes on $L(t) = k(1-R)/n, k = 0,1,\ldots,n$ values. Because of the homogeneity of the CDO portfolio, $L(t)$ will follow a binomial distribution conditional on X:

$$
Q\left[L(t) = \frac{k}{n}(1-R) \mid X = x\right] = \frac{n!}{k!(n-k)!}\, p(t|x)^k (1-p(t|x))^{n-k},\ k = 0,1,\ldots,n \tag{14}
$$

The unconditional portfolio loss density function can be recovered by integrating equation (14) over all possible values of the common factor:

$$
Q\left[L(t) = \frac{k}{n}(1-R)\right] = \int_{-\infty}^{\infty} \frac{n!}{k!(n-k)!}\, p(t|x)^k (1-p(t|x))^{n-k}\, dF_{X(t)}(x),\ k = 0,1,\ldots,n \tag{15}
$$

where $F_{X(t)}(x)$ is the distribution function of the common factor $X(t)$.

For the case when the CDO portfolio is non-homogeneous, one can use semi-analytical techniques to construct the portfolio loss distribution function. In Appendix A, we briefly describe a popular method proposed by Andersen and Sidenius (2003), that calculates the portfolio loss distribution function recursively. Note, that this approach assumes that the recovery rates are the same for all underlying portfolio names. An alternative approach is described by Laurent and Gregory (2003), which uses the characteristic function and Fast Fourier Transform techniques to build the portfolio loss density function. For the case when the initial notionals and the recovery rates of the underlying portfolio names are different see Hull and White (2004) and Andersen and Sidenius (2005).

In the next two sections, we describe the one factor Gaussian and double t copula models. The Gaussian copula will serve as benchmark for the empirical studies, where our principal interest will be to test the double t copula model.

4.2.1 The One Factor Gaussian Copula Model

Different distributional specifications for the common and idiosyncratic factors X_i and E_i from Equation (12) give rise to different factor copula models. The one factor Gaussian copula admits the following specification:

$$V_i = \rho_i X + \sqrt{1-\rho_i^2}\mathscr{E}_i \tag{16}$$

where X and $\mathscr{E}_i$'s are independent and follow the standard normal distribution. Note that we have dropped the time dependence from equation (16), as the standard normal distribution is fully characterized by its mean and variance, which are zero and one, respectively. $|\rho_i| \leq 1$ is generally assumed to be constant, i.e. $\rho_i = \rho, \forall i = 1, \ldots, n$. Hence, the default correlation between two credit names $i \neq j$ will be equal to ρ^2.

As the normal distribution is closed under convolution, the distribution function of any V_i will also be normal. Hence, the default threshold $B_i(t)$ of name i, i.e. the level of the random variable V_i below which the name i defaults, is given by $B_i(t) = \Phi^{-1}(p_i(t))$. Φ is the cumulative distribution function of the standard normal random variable, whereas $p_i(t)$ is given by (11).

The probability that credit name i defaults conditional on a realization of common factor $X = x$ is:

$$p_i(t|x) \doteq Q(\tau_i \leq t|x) = \Phi\left(\frac{\Phi^{-1}(p_i(t)) - \rho\, x}{\sqrt{1-\rho^2}}\right) \tag{17}$$

$\rho = 0$ corresponds to the case when default times are independent, while $\rho = 1$ is associated with the perfect dependence case, meaning that the portfolio behaves like a single credit asset.

4.2.2 The Double T Copula Model

The double t copula model was introduced by Hull and White (2004), and it is a simple extension of the Gaussian copula:

$$V_i = \rho\sqrt{\frac{n_1-2}{n_1}}\,X + \sqrt{1-\rho^2}\sqrt{\frac{n_2-2}{n_2}}\,E_i \tag{18}$$

X and E_i's are pairwise independent student random variables with n_1 and n_2 degrees of freedom, respectively. They are scaled so that each V_i has zero mean and unit variance.

The choice of the student distribution for both common and idiosyncratic factors has certain advantages over the Gaussian one. First, the student distribution has fatter tails, a valuable feature commonly desired in risk management. Second, it exhibits non-zero tail dependence. For any two random variables X and Y with distribution functions F_X and F_Y, the (lower) tail dependence is defined as

$$\lambda_L \;=\; \lim_{u\to 0} Q(X \le F_X^{-1}(u) | Y \le F_Y^{-1}(u)) = \lim_{u\to 0} \frac{C(u,u)}{u}$$

where C is the copula associated with (X,Y).

When X and Y are Student t random variable with equal degrees of freedom, i.e. $n_1 = n_2 = n$, then,

$$\lambda_L \;=\; 2t_n\left(\sqrt{n+1}\,\frac{\sqrt{1-\rho}}{\sqrt{1+\rho}}\right) \tag{19}$$

where t_n is the density function of the Student t random variable with n degrees of freedom (Embrechts et al. (2001)). One can easily show, that this measure is increasing in ρ, and decreasing in n.

Finally, the Gaussian copula is nested within the double t copula model, and can be recovered by letting the degrees of freedom parameters n_1 and n_2 go to infinity. Note, that the lower tail dependence for the Gaussian copula will be zero, i.e. $\lim_{n\to\infty}\lambda_L = 0$.

The conditional default probability $p_i(t|x)$ of name i in the double t copula model, i.e. the probability that name i will default conditional on a realization of the common factor $X = x$, is:

$$p_i(t|x) \;\doteq\; Q(\tau_i \le t|x) = F_{E_i}\left(\frac{B_i(t) - \rho\sqrt{(n_1-2)/n_1}\,x}{\sqrt{1-\rho^2}\sqrt{(n_2-2)/n_2}}\right) \tag{20}$$

where the default barrier is given by

$$B_i(t) = F_{V_i}^{-1}(p_i(t)) \tag{21}$$

and F_{E_i} is the cumulative distribution function of a standard student random variable with n_2 degrees of freedom.

The double t copula model is numerically intensive. To calibrate default barriers $B_i(t) = F_{V_i}^{-1}(p_i(t))$, the distribution function of V_i from equation (18) should be calculated and then inverted. As the student distribution is not closed under convolution, meaning that sum of two independent student random variables is not a student random variables, F_{V_i} should be computed numerically. For instance, Vrnis (2009) describe a numerical method for performing such a task. In case both degrees of freedom parameters are odd, the convolution of two student t random variables can be calculated in closed form. See Walter and Saw (1987) and Berg and Vignat (2008).

5 Data Description

The data that we use for our numerical analysis is based on the iTraxx Europe CDS index and its tranches. The iTraxx European index is managed by Markit, and consists of 125 European CDS contracts, each contract referencing a high grade corporate bond. The underlying index names are equally weighted, which means that the notional amount of each CDS contract is 0.8% of the total portfolio principal. Note, that the index trades like a single CDS contract with a fixed coupon rate and quarterly payments.

The index constituents are updated every six months, a process commonly known as rolling. In the rolling process, the downgraded, illiquid or defaulted CDS contracts are dropped from the index, and are substituted with new liquid CDS names. Hence, the rolling creates a new series which becomes on-the-run until the next rolling date. Earlier created series continue to be traded, but the liquidity is concentrated on the newly created series. Note, that the rolling dates are fixed, and are March 20 and September 20 of each year.

We have the daily data for the mid spreads (average of bid and ask spreads) of the 5-year maturity iTraxx Europe index. This data is provided by Markit. The time period in our sample spans from March 27, 2006 to September 19, 2006, and corresponds to on-the-run Series 5 of the iTraxx Europe index. The overall sample size is 114 days.

We also have the data for standardized tranches of the iTraxx Europe index for Series 5. More specifically, we have the mid daily closing spreads for the (0-3)%, (3-6)%, (6-9)%, (9-12)% and (12-22)% tranches of the index with 5 year maturity. These are commonly known as equity, junior mezzanine, senior mezzanine, senior and super senior tranches. The (0-3)% tranche is quoted differently from the rest of the tranches. It involves an upfront payment made by the protection buyer to the protection seller at the initiation of the tranche contract plus a running spread of 500 basis points (bp) paid quarterly until tranche maturity. Mezzanine and senior tranches have no upfront payments. They are quoted in running spreads (bp) that are also paid quarterly until tranche maturity date. Note, that like the rolling dates, the maturity dates of the iTraxx Europe index or any of its tranches are standardized. For any 5 year contract of Series 5 of the iTraxx European index and its tranches, the fixed maturity date will be June 20, 2011. It means that the actual time to maturity changes a bit for the on-the-run period as we enter into a long/short tranche position from one day to the other in the time period between March 20, 2006 and September 20, 2006.[8]

The data for CDS spreads is taken from Thomson Reuters Datastream. It consists of 5 year CDS spreads for all 125 index constituents and 114 days in our sample. Finally, we have the closing data on EURIBOR rates for all standard maturities plus 2-year, 3-year, 4-year and 5-year swap rates for the European market. This data is taken from Reuters 3000Xtra, and serves to calculate the discount factors.

Table 1 gives the summary statistics for the time series for Series 5 of the iTraxx Europe index and its tranches. The average upfront payment of the equity tranche is 20%, which translates roughly into 900 bp of running spread per annum, as a rule of thumb. With this conversion in mind, we can observe that the tranche spreads decrease monotonically with the tranche attachment/detachment points. The decreasing pattern in the tranche spreads implies that the equity tranche is the riskiest followed by the other tranches in succession.

[INSERT TABLE 1 ABOUT HERE]

Figure 1 depicts the time series for Series 5 of iTraxx Europe index and its tranches. It reveals a generally similar pattern in the times series of the individual tranches. The principal component analysis (PCA)

[8] If one enters into a long/short position in iTraxx or any of its tranches on March 20, 2006, the maturity will be 5.25 years based on the conventional 360 day count (5.25 is the yearly fraction between March 20, 2006 and June 20, 2011). If one goes long/short index or tranche on the last day of the on-the-run period, i.e. September 19, 2006, then the remaining maturity will be 4.75 years. Hence any position entered between March 20, 2006 and September 19, 2006 will have a maturity window between 4.75 and 5.25 years. To keep the things simple, for our numerical analysis we will be using a constant 5 year rolling window for all the tranche maturities and for all days in our sample.

confirms this fact, by showing that the first factor alone account for 83% of the variability in the tranche time series.

[INSERT FIGURE 1 ABOUT HERE]

Average 5 year CDS spread across all 125 names underlying iTraxx Europe index and 114 days in our sample is 32.2 bp, while the time average standard deviation for the 125 names is 21.3 bp. The averaged interval for 125 names across 114 days is from 6 to 145 bp.

6 Empirical Analysis

The double t copula model was first tested by Hull and White (2004). For August 4, 2004 they use the iTraxx Europe and CDX index tranche spreads data, and conclude that the double t distribution copula fits the index tranche spreads reasonably well. Burtschell et al. (2009) find a similar result based on the iTraxx Europe tranche data for February 8, 2005 when comparing several copula approaches. Kalemanova et al. (2007) introduce the Normal Inverse Gaussian (NIG) copula approach and compare the results of their model with those for the double t copula model. For April 12, 2006 they find that the NIG and double t copula models give quantitatively (in terms of the magnitude of the pricing error) and qualitatively (low pricing errors) similar results for the tranche spreads of the iTraxx Europe index. Mortensen (2005) compares the results of the affine jump diffusion (AJD) model of Duffie and Garleanu (2001) with those of the double t copula model, and find that the latter fits best to the market tranche data of DJ CDX index for August 23, 2004.

All these studies base their analysis on single day (non-intra day) data. Wang et al. (2009) provide more extensive empirical analysis using market data on CDX NA index from September 1, 2004 to August 31, 2005. We also do the empirical analysis for a broad time period of 114 days that spans from March 27, 2006 to September 19, 2006. In contrast, we estimate the model for the European credit derivatives market, i.e. for iTraxx Europe index.

In this section we empirically estimate the Gaussian and double t copula models. More specifically, we calibrate the parameters of the models so that the measure of fit (defined below) to the market quotes of the iTraxx Europe tranches is minimized. Note, that the Gaussian copula has only one endogenous parameter, the constant correlation coefficient ρ, while the double t copula model has three such parameters, which are the correlation coefficient ρ and the degrees of freedoms n_1 and n_2 for the factors. Note also, that the exogenous inputs of the models are the CDS spreads of all 125 names underlying the iTraxx Europe index, which are used for the default threshold calibration.

The model calibration process consists of solving for the correlation number ρ and degrees of freedom parameters n_1 and n_2 such that the measure of Relative RMSE is minimized:

$$\min_{\rho,n_1,n_2} \quad \sqrt{\frac{1}{5}\sum_{k=1}^{5}\left(\frac{S_k^{market}-S_k^{model}(\rho,n_1,n_2)}{S_k^{market}}\right)^2} \tag{22}$$

S_k^{market} is the market spread for iTraxx Europe tranche $k = \{[0,3],[3,6],[6,9],[9,12],[12,22]\}$, and $S_j^{model}(\rho,n_1,n_2)$ is the model implied spread for given values of correlation and degrees of freedom parameters:[9]

$$\begin{aligned}
S_{[L_a,L_d]}^{model}(\rho,n_1,n_2) &\approx \frac{\sum_{j=1}^{J} D(t_j)\left[E_{[L_a,L_b]}(t_j)-E_{[L_a,L_b]}(t_{j-1})\right]}{\sum_{j=1}^{J}\Delta t_j D(t_j)\left[1-E_{[L_a,L_b]}(t_j)\right]}\\
E_{[L_a,L_b]}(t) &= \sum_l \mathscr{L}_{[L_a,L_b]}(t,l)\cdot Prob[L(t)=l]\\
\mathscr{L}_{[L_a,L_b]}(t,L(t)) &= \frac{1}{L_d-L_a}\left[(L(t)-L_a)^+-(L(t)-L_d)^+\right]\\
Prob[L(t)=l] &= \vec{f}(\rho,n_1,n_2;\textit{input data})\\
L(t) &= \vec{g}(\textit{input data})
\end{aligned}$$

Though previous studies have considered the case in which the degrees of freedom parameters of the double t copula model are whole numbers, we relax this assumption by calibrating each of n_1 and n_2 to any non-integer number greater than three.[10] In this respect, our analysis can be seen as an extension of Wang et al. (2009), who study the double t copula model with non-integer degrees of freedom parameters, or what they call, double t copula with fractional degrees of freedom. However, there are some differences between their

[9]Note, that all the three parameters ρ, n_1 and n_2 of the double t copula model, implied from the RMSE minimization, are forward looking. For instance, RMSE correlation parameter of 12%, implied from 5 year maturity iTraxx tranche spreads on a particular day, means that the default correlation over 5 year horizon from that day on will be 12%.

[10]We have also done the optimization with the lower bound set to equal 2.01 for both degrees of freedom parameters. However, they hardly give any gain in terms of the reduction of the RMSE measure. Furthermore, the numerical stability of the code, and the computational time for the optimization worsen.

model methodology and estimation and ours. First, they don't use the CDS data on the underlying 125 names of the CDX North American index to calculate the risk neutral default intensities. Instead, they consider the homogeneous portfolio specification, and input the same and constant default intensity of all 125 names as an endogenous variable to the model to be estimated together with the correlation and the degrees of freedom parameters. They also apply the restriction that $n_1 = n_2$, observing that the difference in fit measure between the case when $n_1 = n_2$ and $n_1 \neq n_2$ is negligible. As a fit measure, they consider the total absolute pricing error, which is defined as the sum of the absolute differences between the market spreads and model spreads.

By relaxing the assumption that the degrees of freedom parameters are whole numbers, we are able to capture extra variability in the time series of the implied degrees of freedom parameters, which would otherwise be lost when using only integer degrees of freedom parameters. We also do the calibration separately for the Gaussian copula model (the restrictive case of the double t copula model with $n_1 = n_2 = \infty$ degrees of freedom).

The calibration is done on a daily basis. This is to say, we do the same minimization problem for all 114 days in our sample (from March 27, 2006 to September 19, 2006).

Table 2 reports the summary statistics for the minimized RMSE and the calibrated parameters. The pricing errors for the double t copula model are 14% on average. The minimum and maximum pricing errors are in the range of 6 to 22 percent approximately. The Gaussian copula produces rather high pricing errors of around 68% for the whole sample. Compared to the latter case, the double t copula model on average reduces the pricing errors by 4.9 times.

[INSERT TABLE 2 ABOUT HERE]

Table 3 presents the correlation matrix of the differenced rmse, corr and degrees of freedom parameter series. It reveals relatively high correlation levels between the calibrated series. These results suggest that their is a high inter-dependence among the calibrated parameters of the double t copula model, which should be taken into account in further regression analysis.

[INSERT TABLE 3 ABOUT HERE]

Figure 2 plots the time series of the optimized parameters for the double t copula model. We can observe that the time series of the correlation and n_1 parameters follow nearly the same dynamics, whereas the time series of n_2 evolves inversely with that of n_1.

[INSERT FIGURE 2 ABOUT HERE]

As we have already mentioned before, the literature has considered the double t copula model with integer degrees of freedom parameters. More specifically, many authors have restricted themselves to the case where the degrees of freedom parameters are both equal to 4. To check the validity of this assumption, we carry out a mean test for the degrees of freedom parameters. The hypothesis that the population means of the two degrees of freedom parameters are equal, i.e. $H_0 : E(n_1) = E(n_2)$, is rejected at the 5% error level against the alternative hypothesis $H_a : n_1 \neq n_2$. We also tested the hypotheses that each of the degrees of freedom separately is 4. In the first case, i.e. when $H_0 : E(n_1) = 4$, we fail to reject the null hypothesis at 95% confidence level, whereas we reject the hypothesis that $H_0 : E(n_2) = 4$.

As a next step, we perform a time series analysis of the optimized parameters from Figure 2. For this reason we consider several financial variables that represent major volatility, treasury and corporate bond markets. As a measure of volatility, we use changes in the VIX index. To capture the changes in corporate bond markets, we use the changes in the default spread, where the default spread is defined as the difference between Moody's Aaa and Baa corporate bond yields. Finally, to capture the changes in treasury bond markets we use changes in the term spread, where the term spreads is defines as the difference between one and ten year treasury yields. For the sake of brevity, we will refer (wherever appropriate) to the first differences in VIX volatility index, Moody's default spread, and the Treasury term spread as VIX, DEF, and $TERM$, respectively. Table 4 presents the correlation matrix of our exogenous macro variables. As one would expect, the correlation between changes in the VIX index and term spread is negative, whereas the correlation between default and term spreads is positive. However, the correlation among the employed macro variables are relatively low for the time period that we consider in our analysis.

[INSERT TABLE 4 ABOUT HERE]

As we also want to capture the evolution and the interdependencies between the four calibrated series, our methodology would be to fit a VAR model to the calibrated parameters with the exogenous variables described above.

The following VAR model is fitted to the data:

$$Y_t = \alpha + \sum_{i=1}^{I} \beta_i Y_{t-i} + \sum_{j=0}^{J} \gamma_j X_{t-j} + \varepsilon_t \tag{23}$$

Y_t is the dependent variable vector consisting of the first differences of the correlation, two degrees of freedom parameters, and the rmse. X_t is the exogenous variable vector comprising VIX, $TERM$ and DEF. One-day lag structure ($I = 1$) for the endogenous variables, coupled with the contemporaneous and one-day lagged values of the exogenous variables ($J = 1$) is suggested by the data, which is consistent with the Akaike Information Criterion (AIC).

We use roughly the first 100 observations for the model estimation (in-sample), whereas the last 14 observations are used for the out-of-sample analysis. Table 5 summarizes the VAR estimation results. The VAR results show that the equations for the implied correlation, the first degrees of freedom parameter of the double t copula model and the rmse have significant explanatory power as indicated by the F-tests. However, the significance of the equation for the first degrees of freedom is only at the 10 percent level. The average R^2 statistics for the three significant equations is approximately 33%.

Turning first to the results for the correlation parameter, we observe that the lagged values of VIX are positively related to the correlation parameter *corr*. An increases in the VIX index is often associated with an increase in the volatility of the markets. Hence the positive sign of VIX on correlation seems intuitive, since the volatile markets can contribute to increased number of defaults or default correlation in an economy.

A decrease in the term spread may imply a weakening economy. According to this argument, an increase in the term spread may decrease the CDS spreads of the underlying names of the iTraxx Europe index. Decreasing CDS spread can decrease the default correlation between the companies of the iTraxx Europe index. Hence, the negative and significant coefficient sign of $TERM$ in the equation of *corr* seems reasonable.

Turning next to corporate bond markets, we see that default spread DEF has a significant and positive relationship with correlation. This can be intuitive as higher default spreads can induce higher default correlation.

Changes in model mispricing, measured by the RMSE can be explained by the lag of changes in the VIX index, changes in the term spread $TERM$, and lagged changes in the second degrees of freedom of the double t copula model n_2. The negative coefficient of the VIX index might imply that the double t copula model captures better the tranche spreads of the iTraxx Europe index when the investors anticipates volatile market conditions over future time horizons. On the other hand, the positive sign of the $TERM$ variable indicates that the pricing power of the model is worse during expected good economic conditions. The positive coefficient sign of the second degrees of freedom parameter of the double t copula model n_2 seem to confirm this result. The second degrees of freedom parameter of the double t copula model n_2 represents the idiosyncratic factor specific to each company underlying the iTraxx Europe index. The higher n_2, the lower the volatility of each idiosyncratic factor. Hence, the positive sign of the coefficient of n_2 in the *rmse* equation indicates that as the volatility of the idiosyncratic factor specific to each company decreases, the double t copula model captures worse the tranche spreads of the iTraxx Europe index.

Some of the coefficients of the macro variables are statistically significant in the equations for the degrees of freedom parameters. However, those coefficients are difficult to interpret. Additionally, as noted above, the equation for the second degrees of freedom parameter does not have any explanatory power, whereas the significance of the explanatory power of the equation for first degrees of freedom is only at 10 percent level.

In short, higher market volatility, default spreads and lower term spreads can lead to higher default correlation among the companies underlying iTraxx Europe index. On the other hand, the results on the rsme suggest that the double t copula captures better the tranches of iTraxx Europe index for expected bad times than for good times.

[INSERT TABLE 5 ABOUT HERE]

Figure 3 plots the out-of-sample forecast for the calibrated parameters along with their observed values from the time period between September 1, 2006 and September 19, 2006. The predictive power of the proposed VAR model seems to be satisfactory.

[INSERT FIGURE 3 ABOUT HERE]

7 Conclusion

In this paper we have examined the ability of the double t copula model of Hull and White (2004) to replicate the market spreads of iTraxx Europe index tranches based on the data from March 27, 2006 to Septeber 19, 2006. Compared to the one factor Gaussian copula, this model reduces pricing errors on average by more than four times. We also obtain that the degrees of freedom parameters implied from the double t copula model, are time varying and different one from the other.

VAR analysis of the double t copula model parameters reveal that the correlation and the degrees of freedom parameters can be explained by major financial variables, such as the volatility index VIX, the default and the treasury term spreads. Particularly, the results of the equation of the implied correlation parameter suggest that an increase in the VIX index and the default spread can lead to higher default correlations among the companies underlying the iTraxx Europe index, whereas an increase in the term spread can lead to lower default correlation among those companies. The RMSE, which is the mispricing measure of the double t copula model, can be explained by such macro variables as the volatility index VIX and the term spread. In particular, the results of the rmse seem to suggest that the model can capture better the tranches of the iTraxx Europe index during bad than good times. The out-of-sample analysis of the calibrated parameters of the double t copula model show reasonable forecasting power of the above mentioned exogenous variables for the correlation, the two degrees of freedom and rmse parameters.

A logical extension of this paper will be to broaden our sample period. Another way to go would be to do the same exercise for the North American CDS market CDX, and compare the results with those presented in this paper.

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Table 1: Summary Statistics of iTraxx Europe Index and its Tranches

	Panel A: Summary Statistics							
	mean	sd	skew	kurt	min	med	max	N
iTraxx EU index	30.54	2.31	0.09	2.01	26.53	30.53	35.62	114
(0-3)% Tranche	20.46	2.94	-0.01	2.06	14.80	20.30	26.80	114
(3-6)% Tranche	65.28	11.91	0.04	1.79	43.52	66.33	90.99	114
(6-9)% Tranche	18.48	3.24	0.02	1.89	12.12	18.78	24.86	114
(9-12)% Tranche	8.55	1.62	0.04	2.30	4.90	8.24	11.59	114
(12-22)% Tranche	3.66	0.48	-0.07	1.86	2.68	3.77	4.74	114

	Panel B: Correlation Matrix					
	index	(0-3)%	(3-6)%	(6-9)%	(9-12)%	(12-22)%
index	1					
(0-3)%	0.978	1				
(3-6)%	0.864	0.766	1			
(6-9)%	0.828	0.728	0.972	1		
(9-12)%	0.663	0.555	0.833	0.888	1	
(12-22)%	0.864	0.834	0.756	0.767	0.746	1

This table reports summary statistics for Series 5 of iTraxx Europe index and its tranches with 5 years of maturity for the time period from March 27, 2006 to September 19, 2006. Equity tranche is quoted up-front (%), while the index and the rest of tranches in running spreads (bp).

Table 2: Summary Statistics of Parameters of Gaussian and Double T Copula Models

	Panel A: Gaussian Copula Model							
	mean	sd	skewness	kurtosis	min	med	max	N
RMSE	0.6815	0.0424	-0.1884	1.9115	0.5972	0.6819	0.7529	114
ρ_G	0.1088	0.0133	-0.1393	2.2349	0.0730	0.1088	0.1332	114

	Panel B: Double T copula Model							
	mean	sd	skewness	kurtosis	min	med	max	N
RMSE	0.1395	0.0457	-0.0175	1.7320	0.0551	0.1390	0.2200	114
ρ_T	0.1220	0.0105	0.1589	2.6050	0.0991	0.1206	0.1447	114
n_1	3.8837	0.5861	0.6486	2.3380	3.0000	3.6307	5.2559	114
n_2	4.1512	1.3138	1.6582	6.0225	3.0004	3.6796	9.3409	114

Descriptive statistics for the calibrated parameters of the Gaussian and Double t copula models. The upper panel corresponds to the Gaussian copula model, while the lower panel is for the double t copula. The time period goes from March 27, 2006 to September 19, 2006.

Table 3: Correlation Matrix of Parameters of Double t Copula Model

	Δ rmse	Δ corr	Δ df1	Δ df2
Δ rmse	1			
Δ corr	-0.535	1		
Δ df1	-0.345	0.902	1	
Δ df2	0.236	-0.857	-0.833	1

This table displays the correlation matrix of the differenced series of rmse, correlation, and degrees of freedom parameters implied from the double t copula model. The period is from March 27, 2006 to September 19, 2006.

Table 4: Correlation Matrix of Macro Variables

	Δ VIX	Δ TERM	Δ DEF
Δ VIX	1.0000		
Δ TERM	-0.0075	1.0000	
Δ DEF	0.0704	0.0747	1.0000

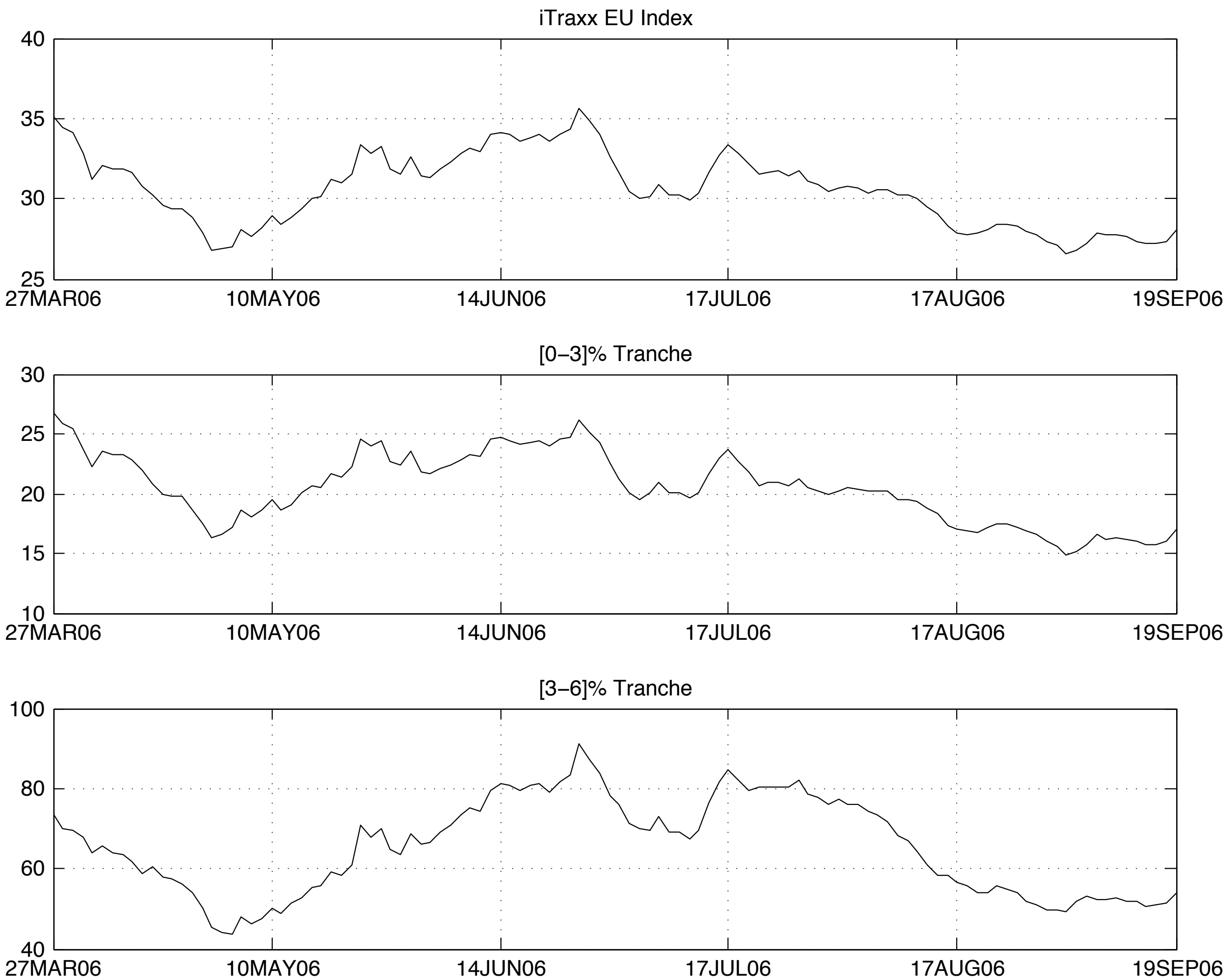
This table displays the correlation matrix of the differenced series of the VIX index, the slope of the term structure of interest rates, and the Mooody's default spread. The period is from March 27, 2006 to September 19, 2006.

Table 5: VAR Results of Parameters of Double T Copula Model

	Δ_t corr	Δ_t df1	Δ_t df2	Δ_t rmse
Δ_{t-1} corr	-1.50	0.21	-0.12	1.62
Δ_{t-1} df1	0.49	-0.30	-0.16	-0.02
Δ_{t-1} df2	-1.14	0.32	-1.00	2.46**
Δ_{t-1} rmse	0.23	0.63	-0.22	-0.31
Δ_t VIX	-0.64	-1.93*	0.63	-0.05
Δ_{t-1} VIX	2.90***	2.48**	-1.72*	-3.83***
Δ_t TERM	-1.68*	-0.92	0.88	1.96**
Δ_{t-1} TERM	-0.40	-1.20	0.26	-1.09
Δ_t DEF	2.04**	2.62***	-1.99**	0.19
Δ_{t-1} DEF	-1.32	-0.87	1.40	0.91
R^2	0.3259	0.2481	0.1780	0.3939
$P > F$	0.0060	0.0783	0.3544	0.0003

This table reports the VAR results of the double t copula model parameters calibrated for the time period from March 27, 2006 to September 19, 2006. Δ_t denotes the first difference, while Δ_{t-1} denotes the first lag of the differenced variable ($\Delta_t\ x \doteq x_t - x_{t-1},\ \Delta_{t-1}\ x \doteq x_{t-1} - x_{t-2}$). A first order VAR structure is suggested by the data, where the exogenous variables are taken with their contemporaneous and one lag values (i.e., $I = 1$ and $J = 1$). The superscript denotes the significance level. *** denotes significance at the 1% level; ** denotes significance at 5% level; * denotes significance at 10% level. $P > F$ is the p-value of the F test of the hypothesis that the coefficients of all the variables are jointly zero.

Figure 1: Time Series of iTraxx Europe index and its Tranches



This figure graphs the time series for Series 5 of iTraxx Europe index and its tranches from March 27, 2006 to September 19, 2006. Equity tranche is quoted up-front (%), while the index and the rest of tranches in running spreads (bp).

Figure 1: Continued

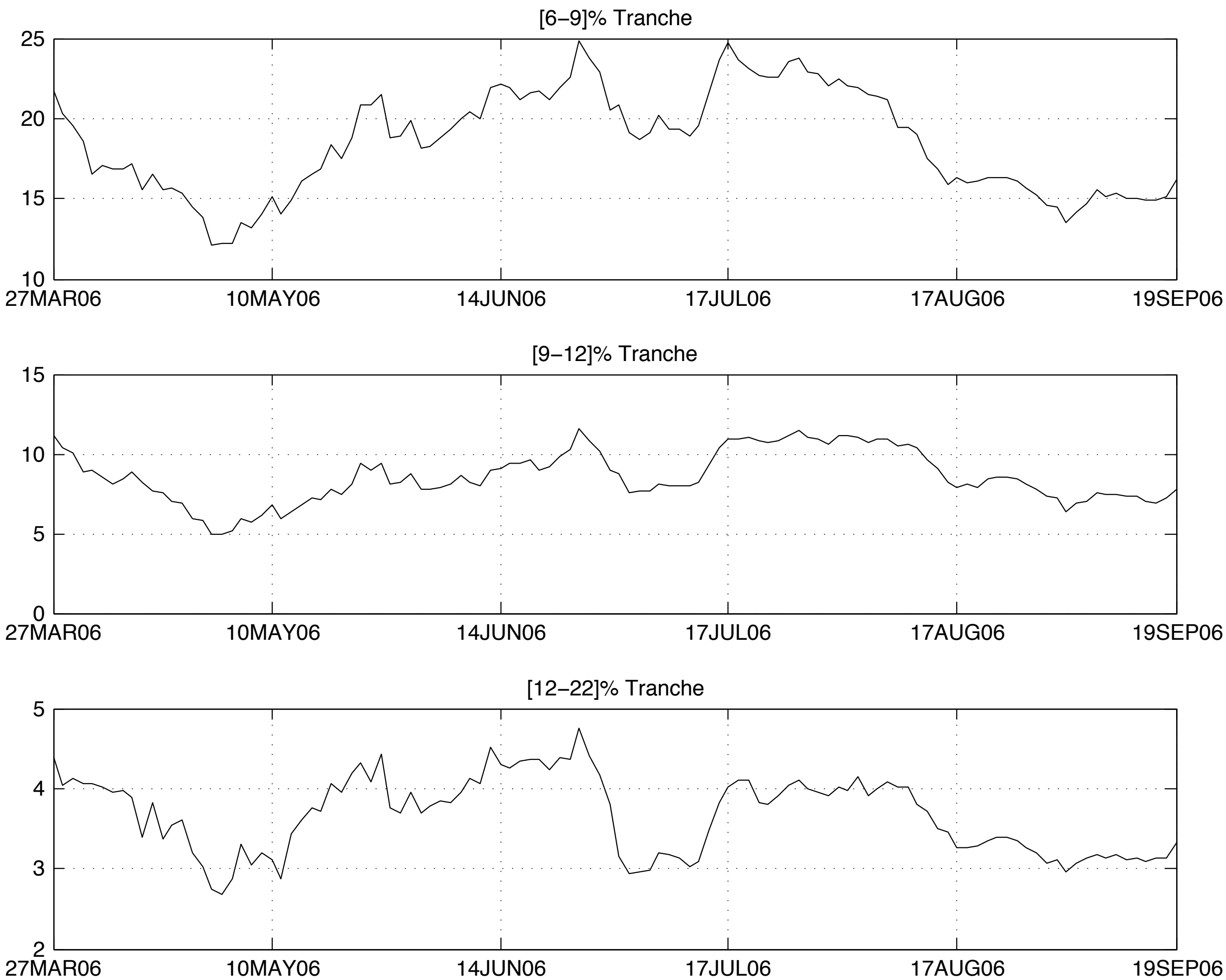
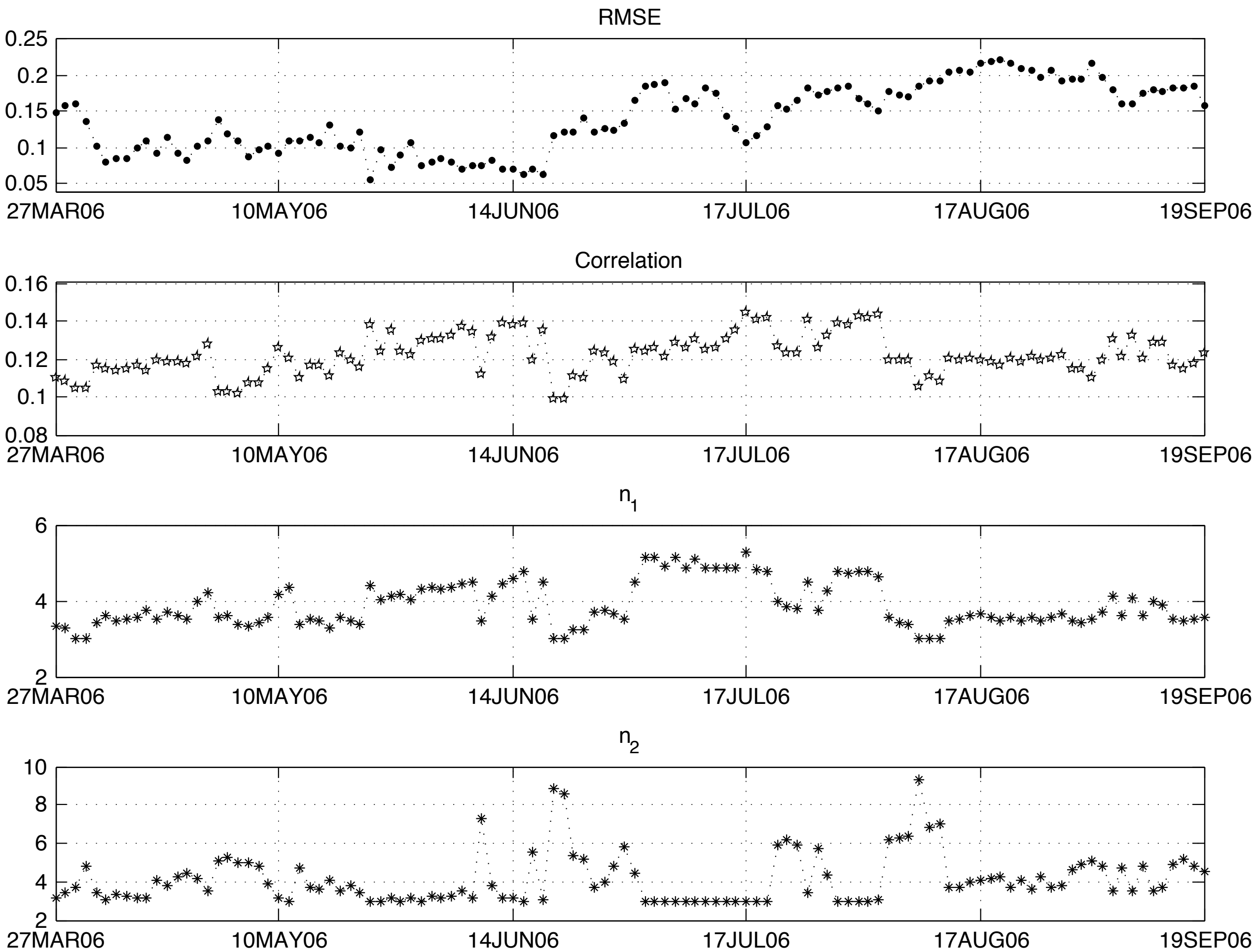
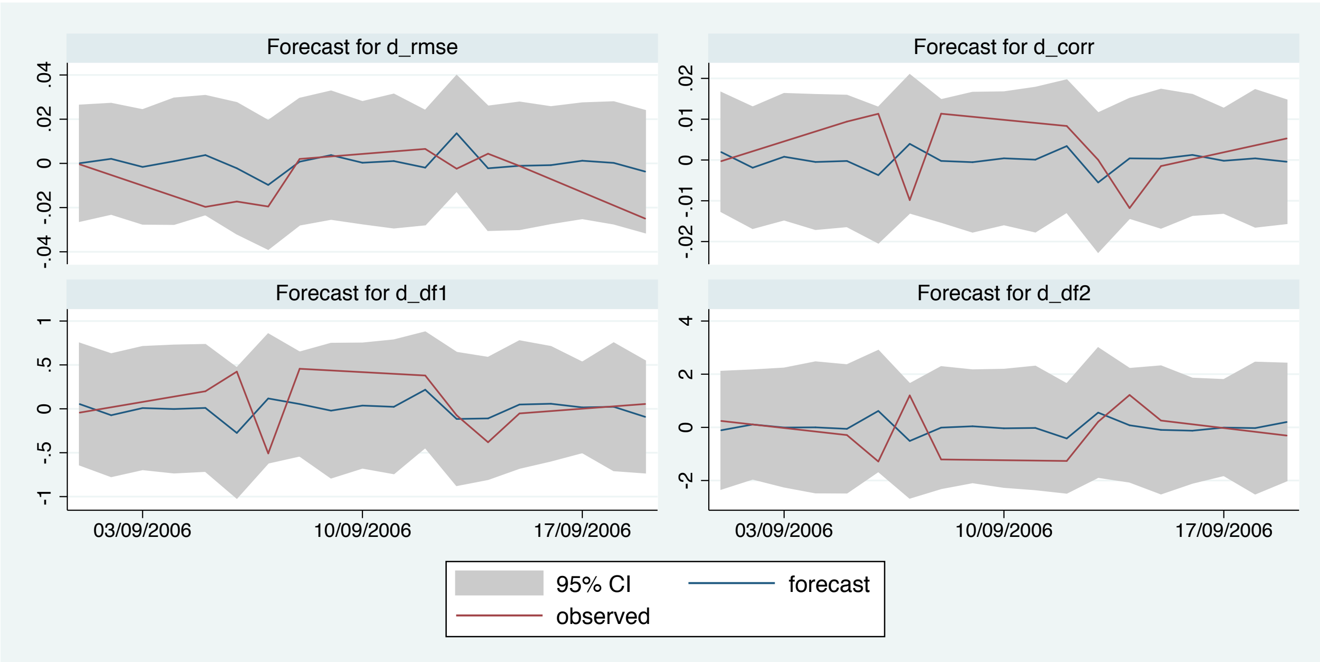


Figure 2: Time Series of Parameters of Double T Copula Model



This figure graphs the optimized parameter space for the double t copula model. More specifically, the upper panel plots the optimal RMSEs across for the double t copula model. The middle and the lower two bottom panels depict the corresponding correlation coefficient and the optimal number of the degrees of freedom parameter graphs that produce the optimized RMSEs of the upper panel. The sample ranges from March 27, 2006 to September 19, 2006.

Figure 3: Out-of-Sample Graph



This figure graphs the out-of-sample forecasts for the calibrated parameters of the double t copula model. The out-of-sample ranges from September 1, 2006 to September 19, 2006.

A Computation of CDO Portfolio Loss Distribution

This section describes briefly the method of Andersen and Sidenius (2003) that uses a recursive algorithm to build up the CDO portfolio loss distribution function. Let $p_1(x), p_2(x), \dots p_n(x)$ be default probabilities of n obligors conditional on a realization of the common factor $X = x$. Let's additionally denote by $P_n^k(x)$ the conditional probability of having k defaults in an n credit portfolio. Finally, the recovery rate R is assumed to be constant across all credit names in the portfolio.

If the portfolio consists of one credit, let's say credit 1 with conditional default probability $p_1(x)$, then the probability of having no default in portfolio is $P_1^0(x) = 1 - p_1(x)$, while the probability of observing 1 default is $P_1^1(x) = p_1(x)$. If we add one more credit to the portfolio, then three scenarios are possible. First, no name in portfolio defaults with probability $P_2^0(x) = P_1^0(x) \cdot (1 - p_2(x))$. Second, there is only one default in portfolio with probability $P_2^1(x) = P_1^1(x) \cdot (1 - p_2(x)) + P_1^0(x) \cdot p_2(x)$. Finally, all two names in portfolio default, where the probability of this event is $P_2^2(x) = P_1^1(x) \cdot p_2(x)$.

By induction method it can be shown that when one more credit is added to a current n credit portfolio, then

$$P_{n+1}^k(x) = \begin{cases} P_n^k(x) \cdot p_n(x) & \text{if} \quad k = 0 \\ P_n^k(x) \cdot (1 - p_{n+1}(x)) + P_n^{k-1}(x) \cdot p_{n+1}(x) & \text{if} \quad k = 1, 2 \dots, n \\ P_n^k(x) \cdot p_{n+1}(x) & \text{if} \quad k = n+1 \end{cases}$$

The unconditional default probability of having k defaults in an n credit portfolio can be calculated by averaging the above expression over all possible values of X:

$$P_n^k = E(P_n^k(X)) = \int_X P_n^k(x) f_X(x)\, dx;\ \forall k = 0, 1, 2, \dots, n$$

Because we assumed a constant recovery rate R, the portfolio Loss Given Default (LGD) in percentage terms would be $L = k/n \cdot (1 - R),\ k = 0, 1, \dots, n$

Chapter 2

On the effects of illiquidity in CDS spreads

Abstract

This article explores the impact of liquidity supply on Credit Default Swap (CDS) spreads. Our sample comprises a CDS panel with more than 280 US firms during the period of 2004-2011. We proxy the CDS liquidity with several measures such as bid-ask spreads, gamma measure and liquidity scores, among others. We characterize the relationship between liquidity and default swap spreads in two ways: first, we perform a panel data analysis to study the cross-sectional dynamics between our liquidity proxies and plain CDS spreads. Second, we examine whether liquidity is priced by CDS investors by examining the interactions between our liquidity proxies and the risk premium and default components embedded in CDS spreads. Our results indicate that bid-ask spread, gamma and return-to-volume measures are important factors in explaining illiquidity of both CDS spreads and risk premium. The usefulness of the number of contributors and Fitch liquidity score as measures of liquidity is weak.

1 Introduction

Credit Default Swap (CDS) contracts allow to trade on and transfer the credit risk of a company. Traditionally, CDS spreads represent the fair insurance price for the credit risk of a company. Because of their contractual nature, CDS contracts are less influenced by convenience or liquidity factors than bond assets (Longstaff et al., 2005). However, recent empirical evidence suggests that CDS spreads may not be fully explained by credit risk factors related to the underlying company (Collin-Dufresne et al. (2001), Blanco et al. (2005), Tang and Yan (2008) or Fulop and Lescourret (2007), among others). Additionally, the soaring CDS spreads during the financial crisis of 2007-2011 raise the question of whether CDS prices are affected by factors other than default risk. Given the central role of CDS markets nowadays in assessing the creditworthiness of firms and institutions and their ability to lead other markets (see Blanco et al., 2005; Forte and Peña, 2009), this question is of paramount importance.

This article assesses the relevance of liquidity in default swap contracts when investors are hedging/trading under financially distressed conditions. We hypothesize that liquidity is an important element in CDS spreads for several reasons: first, liquidity can be a significant factor in default swap contracts due to the over-the-counter (OTC) nature of CDS markets. There is no central organized place or exchange where trading orders are matched. Instead, a CDS market operates through a decentralized and opaque dealer network[1]. As a consequence, costs of search and other frictions can be comparatively high relative to other markets, resulting in lower liquidity in OTC derivative markets (Duffie et al., 2007).

Other factors such as information asymmetries suggest that liquidity plays an important role in CDS markets. For instance, Acharya and Johnson (2007) find evidence of insider trading in credit derivatives markets. They argue that many banks and financial institutions trade CDS of companies for whom they provide financing. Therefore, CDS contracts allow those banks to exploit private information about their clients which is not available to the public. As a result, the asymmetry of information can lead to reduced liquidity (see, for instance, Easley et al. (1996) or Brockman and Chung, 2003). As pointed out by Acharya and Johnson (2007), credit derivative markets may be especially vulnerable to asymmetric information and insider trading problems because most of the players in CDS markets are insiders.

[1]The trades are usually initiated either by a phone call between the counter-parties or they are conducted through interdealer brokers (IDB). Dealers can place the quotes with the IDB house, where the interdealer brokers match the dealers and then execute the trade.

Last but not least, the CDS market is an opaque market controlled by a small number of financial institutions.[2] This fact has implications for liquidity as small markets are likely to be less competitive, and hence less liquid. The reason for the small number of market players may be the high cost of entry into CDS markets. During the second half of 2010, the CDS market constituted approximately 5% of the OTC derivatives market in terms of the notional amount outstanding. In nominal terms, the total amount outstanding of CDS market was 29.9 trillion US dollars as opposed to 601.1 trillion US dollars of the overall OTC derivatives market (see BIS(2011) May report).

We analyze empirically the relationship between CDS spreads and liquidity. We proxy liquidity using a number of measures such as absolute bid-ask spread and the number of contributors (NOC) providing quotes to Markit. Additionally, we also introduce three new illiquidity proxies such as i) the CDS gamma measure, inspired by the bond illiquidity measure of Bao et al. (2011), ii) the return-to-volume illiquidity measure, a version of Amihud (2002) stock illiquidity variable and iii) the Fitch liquidity score, a synthetic indicator of liquidity provided by Fitch. Our analysis is based on a comprehensive panel of CDS spreads for 283 US firms taken from Markit. Our dataset consists of a diversified sample of CDS names across different rating categories and sectors for a time period that spans from January 2004 to April 2011, covering the recent financial crisis period. Moreover, we have an access to an extensive data on bid-ask spreads and default probabilities from CMA Datastream and Moody's, respectively.

Our study is developed in two parts. First, we conduct a panel data analysis in order to study the cross-sectional relationship between changes in our liquidity proxies and plain CDS spreads, respectively. Second, we examine whether liquidity is a risk factor priced by CDS investors. For this reason, we analyze the relationship between our liquidity proxies and the default and risk premium components of default swap spreads. The risk premium denotes the compensation demanded by protection sellers that is associated with the unpredictable changes in the default risk environment. This premium is also known as *distress* risk premium as opposed to *default event* premium, which embodies the reward for changes in the bond price in the event of default (see Driessen (2005) or Berndt et al., 2008). An in-depth discussion about the risk premium within the intensity framework of Duffie and Singleton (1999) can be found in Jarrow et al. (2005) and Yu (2002). Using the methodology developed by Pan and Singleton (2008) and also applied by Longstaff et al. (2011), we are able to disentangle how much of the CDS spreads are due to compensation via distress

[2] See "EU hits banks with credit default swap probe", Reuters, April 29, 2011

risk premium or pure effects of default.

Our results show a strong and significant relationship between changes in illiquidity proxies and changes in default swap spreads. On the one hand, we find that changes in liquidity measures such as absolute bid-ask spread, return-to-volume and gamma measure of illiquidity of CDS names are significant determinants for changes in CDS spreads during the period of 2004-2007. Moreover, illiquidity measured by bid-ask spreads intensifies as the credit crisis worsens. On the other hand, changes in number of contributors and Fitch liquidity score exhibit a significant statistical relationship with changes in CDS spreads. However, we find an inverse relationship between the latter variables that still puzzles us. Additionally, our results on the two components of CDS spreads, risk premium and default risk, also show a significant interaction between CDS constituents and our liquidity proxies.

We document a consistent deviation in the parameters governing the dynamics of the instantaneous, risk-neutral arrival rate of a credit event ($\lambda^{\mathbb{Q}}$) under risk neutral ($\mathbb{Q}$) and physical ($\mathbb{P}$) measures in the corporate CDS market. We impose an Ornstein-Uhlenbeck (OU) mean-reverting structure for the logarithm of the risk-neutral default intensity $\lambda^{\mathbb{Q}}$. The Maximum Likelihood (ML) model estimates reveal a strong high (low) mean-reversion rate under $\mathbb{P}$ ($\mathbb{Q}$) measures. To put these findings into perspective, investors anticipate a worsening credit-risk environment through time. Pan and Singleton (2008) also interpret this fact as evidence that an important fraction of systematic risk is being priced via the distress premium in the context of sovereign CDS markets. According to our results, the risk premium (on average) ranges from 22.24 bps for AA-rated companies to 254.09 bps for B-rated companies. In terms of their relative contribution, the risk premium represents around 28% (42%) of the total AA(B)-rated firm CDS spread. Surprisingly enough, the relative contribution of risk premia to overall CDS spreads (on average) is around 40% when firms are grouped by sectors, with the sole exception of 10% for Financials. How much of this gain in risk premium is due to liquidity factors is a matter of interest in our study.

Our results on the effect of liquidity contribute to a research area that is very active nowadays.[3]. From a theoretical perspective, the problem of frictions in OTC markets has been studied by Lagos et al. (2011) and Brunnermeier and Pedersen (2009). Empirically, Ericsson and Renault (2006), Bao et al. (2011) and Lin et al. (2011) have analyzed liquidity concerns in corporate bond markets. The studies of Tang and Yan (2008) and

[3]The literature about liquidity in equity derivatives markets has received an active attention in the past. However, those articles analyzing the liquidity in default swap markets are yet scarce. Paradoxically, the CDS outstanding has been two times bigger than the equity derivatives in 2004. This difference has widened to *four* times in 2010 (ISDA, survey results 01/1987-06/2010).

Bongaerts et al. (2011) focus on the CDS market. This article mainly continues and extends Tang and Yan (2008), who also explore the interaction between liquidity and CDS spreads. Our paper differs from Tang and Yan (2008) by providing a model that quantifies the risk premium inherent in CDS spreads. Additionally, we employ a more recent sample period which includes the recent financial crisis. Having obtained a measure of risk premia, we examine how it relates to liquidity factors. Some standard references on analyzing the risk premium in the corporate bond markets are the works of Duffee (1999) and Driessen (2005). Berndt et al. (2008) and Longstaff et al. (2005) employ corporate CDS spreads in order to extract information about risk premia. Our approach is mainly inspired by Pan and Singleton (2008) and Longstaff et al. (2011), who extract the risk premia from sovereign CDS spreads. By contrast, the empirical studies about the link between default risk and liquidity remains scarce. To the best of our knowledge, this article is pioneering in assessing the relationship between CDS spread constituents and liquidity.

To summarize, this article analyzes the impact of CDS liquidity supply on both plain CDS spreads and the risk premia embedded in them. The remainder of the article is structured as follows: Section 2 overviews the default swap market and presents our dataset. Sections 3 and 4 discuss the liquidity variables and their relationship with CDS spreads, respectively. Sections 5 introduces the decomposition technique of Pan and Singleton (2008), providing some results about the CDS constituents. The effects of liquidity on risk premium and default components are studied in Section 6. Finally, Section 7 concludes.

2 The CDS Market

This section describes the structure of CDS markets, and characterizes the general features of a CDS contract. We also summarize the main characteristics of our data sample.

2.1 The structure of the CDS market

The CDS market has been one of the fastest growing OTC derivative markets before the start of the financial crisis in August 2007. Figure 1 shows the size of the CDS market in terms of its notional amount outstanding (upper graph) and gross market value (lower graph), respectively. The notional amount is similar to bond principal amount. However, unlike bonds, there is no exchange of notional during the life of the contract. The notional amount serves a reference on which contractual payments for a CDS contract are based. Figure

1 (b) offers a different perspective on CDS markets. It displays the gross market value of CDS contracts, that is, the absolute sum of all open CDS contracts evaluated at market prices on the reporting date. Gross market value provides a measure of the potential market risk in CDS transactions. Both graphs are constructed based on the data from the BIS semi-annual reports on OTC derivatives market.

[INSERT FIGURE 1 ABOUT HERE]

Figure 1 shows that the size of the CDS market in terms of the notional amount outstanding (upper graph) was USD 6.4 trillion by December 2004. It peaked to USD 58.2 trillion by December 2007, constituting around 10% of the overall OTC market size in terms of notional outstanding. After the second half of 2007, the CDS market gradually declined up to USD 32.4 trillion during June 2011 (BIS, 2012). On average, the CDS market has constituted around 5% of the overall notional OTC derivatives market over this period. In terms of gross value (lower graph), the default swap market has increased considerably after June 2007, rising from USD 2.2 trillion up to USD 5.1 trillion during the second half of 2008. Since December 2009, the average value of all CDS marked-to-market positions remains stable around USD 1.54 trillion.

Credit derivative (CD) contracts can also be classified into single- and multi-name contracts. During the first half of 2011, multi-name CD contracts, such as basket default swaps, CDS indexes, tranche index products and collateral debt obligations accounted for 45% of CD market share (on average). On the other hand, single name CDS contracts accounted for 55% of the overall CD market, where corporate (non-sovereign) CDS contracts represented the 85% of the total –about USD 18.1 trillion in nominal amount. In terms of maturity, single name default swaps with maturities ranging from 1 to 5 years accounted for the 70% of the single name CDS market share. In terms of rating, investment grade single name CDS contracts (AAA-BBB) constituted approximately 70% of the single name CDS market.

With regard to the composition of market participants, reporting dealers (commercial and investment banks, securities houses) accounted for 60% of the single name CDS market involvement for the first half of 2011. Other financial and non-financial institutions (insurance firms, hedge funds, etc.) represented the remaining 39% and 1% of trading in CDS markets, respectively. The overall picture is similar for earlier time periods. Thus, the CDS market seems to be mainly dominated by investors that operate in the financial sector.

2.2 CDS definition

A Credit Default Swap (CDS) is a derivative contract that hedges the credit risk of an underlying company that it references (also known as reference entity). It is an agreement between two parties, where one party (protection buyer) agrees to make periodic payments to the other party (protection seller) until the contract maturity or some predefined credit events, whichever occurs first. CDS spreads are quoted in basis points per annum of the total notional amount. The frequency of payments for corporate CDS names is mostly quarterly. In case the credit event occurs before CDS maturity, and assuming physical settlement, the protection buyer delivers the defaulted bonds to the protection seller and receives the face value of the contract principal. In case of cash settlement, the protection seller compensates the protection buyer by paying the difference between the notional amount of the CDS contract and the market value of the distressed bonds for the same notional amount. Physical delivery is the dominant type of settlement in the CDS market.

The credit events that trigger payments are specified in the CDS contract. The International Swaps and Derivatives Association (ISDA) defines several types of credit events, which generally include bankruptcy, failure to pay and restructuring.[4] Currently, there are four types of restructuring defined by ISDA: full restructuring (FR - any restructuring constitutes a credit event, and any bond of maturity up to 30 years is deliverable), modified restructuring (MR - restructuring counts as a credit event, and any bond of maturity 30 months or less is deliverable after the termination date of the CDS contract), modified-modified restructuring (MM - any bond of maturity shorter than 60 months for restructured obligations and 30 months for all other obligations is deliverable), and no restructuring (NR - no restructuring events constitute a credit event). The MR clause is most common in US market, whereas in Europe the most common one is the MM clause. The most frequently quoted and traded CDS contracts are the ones with 1-, 3-, 5- , 7- and 10-year maturities. The typical notional amount of a CDS contract is USD 5-10 million for investment grade firms, and USD 2-5 millions for high yield names.

To price a CDS, let us consider a CDS contract with maturity M and annualized premium payment $CDS(M)$. Additionally, assume the premium payments are made quarterly. Then, the CDS spread at time t

[4] The restructuring has been a major source of controversy among the CDS market participants. The reason is that restructuring of debt may not constitute a loss for the protection buyers. See O'Kane et al. (2003).

with M year maturity will be computed as

$$CDS_t^Q(M) \quad = \quad \frac{4L^{\mathbb{Q}} \int_t^{t+M} E_t^{\mathbb{Q}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u (r_s + \lambda_s^{\mathbb{Q}}) ds} \right] du}{\sum_{i=1}^{4M} E_t^{\mathbb{Q}} \left[e^{-\int_t^{t+.25i} (r_s + \lambda_s^{\mathbb{Q}}) ds} \right]}, \tag{1}$$

where r_t denotes the risk-free rate, $\lambda_t^{\mathbb{Q}}$ is the intensity of the Poisson process governing default, and $L_t^{\mathbb{Q}}$ is the loss given default of the referenced bond under the $\mathbb{Q}$ measure. The dynamics of $\lambda_t^{\mathbb{Q}}$ process are discussed in Section 5.

The numerator in equation (1) represents the expected payments to the protection buyer in case of default. The denominator reflects the discounted value of a constant, risky annuity of USD 1 paid quarterly until maturity or default, whichever comes first. At the moment of inception, the premium on this risky annuity (the CDS spread) paid by the protection buyer must equal the expected discounted payments faced by the protection seller. Without loss of generality, the notional amount of the CDS contract is normalized to one. This implies a loss given default equal to $1-R$, where R is the recovery rate of the underlying bond in case of default. Expression (1) is similar to those employed in Pan and Singleton (2008) and Longstaff et al. (2011).

Throughout the paper we assume that the risk-free rate and the default intensity processes are independent from each other. Additionally, we use a constant recovery rate, and assume it is the same under both actual $\mathbb{P}$ and risk-neutral $\mathbb{Q}$ measures. Both are standard assumptions in the credit risk literature.

2.3 CDS Data

We obtain the data on CDS spreads form Markit Group Ltd., a data provider which collects quotes from more than 30 major participants[5]. Our dataset comprises daily quotes (composite average of bid-ask quotes) of CDS spreads with 1-, 3-, 5-, 7-, and 10-year maturities. We consider North American CDS names that are or have been constituents of the CDX index. Additionally, we only consider contracts that are denominated in USD with the modified restructuring (MR) clause. We conduct our empirical analysis based on monthly CDS spreads. To this end, we take the last non-missing CDS spread of a given month. Our final sample is comprised of a panel of 283 CDS names across six different rating groups (from AA to CCC) and ten sectors (basic materials, consumer goods, consumer services, financial, health care, industrial, oil&gas, technology,

[5]Mayordomo et al. (2011) provide a detailed description of Markit. They also refer to some academic articles employing this database.

telecommunications and utilities). The time period spans from January 2004 to April 2011 and it comprises more than 100,500 daily observations.

Table 1 describes the distribution of CDS names by sector and rating. Around 52% of our sample are investment grade companies with AA (2%), A (17%) and BBB (33%) ratings, respectively. The Consumer Services sector accounts for almost 26% of the firms, followed by Financials (15%), Consumer Goods (14%) and Industrials (11%).

[INSERT TABLE 1 ABOUT HERE]

Table 2 provides the summary statistics of CDS spreads by rating and maturity. On average, CDS spreads increase both across ratings and maturities for the overall sample. Similar results apply to their median values. Standard deviations of CDS spreads rise as the credit ratings of the underlying CDS names deteriorate. Interestingly, CDS contracts with short-term maturity exhibit more volatility in CDS spreads than CDS contract with long-term maturity. Maximum values of CDS spreads are unrealistically high, which suggests presence of outliers in CDS spreads.

Table 2 also suggests that CDS term structure can be inverted. More specifically, we observe that CDS spreads with lower maturities can be higher that CDS spreads with longer maturities. For instance, Schneider et al. (2009) argues that since investment funds primarily use 1-year CDS to express views on the creditworthiness of a CDS name, the economic driver behind the unique pattern in 1-year spreads is a supply-and-demand premium induced by such large trades.

[INSERT TABLE 2 ABOUT HERE]

Figure 2 depicts the monthly time series of CDS spreads by rating group. The time series of each rating group is calculated by taking the cross sectional average of CDS spreads for each month and rating group. Before the aggregation we drop the CDS spreads that fall outside the 1st and 99th percentile of the distribution of pooled CDS spreads. The vertical shadowed lines mark two key events of the financial crisis: i) August 2007, when BNP Paribas frozen three funds because of the subprime assets[6] and ii) the Lehman Brothers collapse in September 2008 [7]. On average, Figure 2 shows that the CDS spreads for investment grade companies are much lower and less volatile than the CDS spreads for high-yield companies. Additionally, spreads

[6]See "BNP Paribas suspends funds because of subprime problems", NYT, August 7, 2007.
[7]See "Lehman Files for Bankruptcy; Merrill Is Sold", NYT, September 14, 2008.

exhibit a high commonality across ratings. There is a noticeable break in the dynamics of the CDS spreads before and after August 2007. The time period before August 2007 can be characterized as a period with stable and low volatility CDS spread dynamics, with the exception of spreads for CDSs of high-yield names. In contrast, after the start of the financial crisis of August 2007, CDS spreads exhibit an uneven pattern .

[INSERT FIGURE 2 ABOUT HERE]

3 The Liquidity of CDS spreads

3.1 Liquidity Proxies

When trying to assess the liquidity of CDSs, our objective is to capture the ease with which one can initiate or unwind a CDS position. Each CDS trade has certain costs associated with it, such as search costs, broker/dealer commissions and asymmetry of information costs (Acharya and Johnson, 2007). The higher these costs, the higher the illiquidity of the corresponding CDS contract. Bongaerts et al. (2011) provides a theoretical approach to model the interaction between hedging demand and liquidity premium.

Since liquidity is an economic variable not directly observed in the markets, we construct several measures in order to capture certain aspects of CDS liquidity. More specifically, we proxy liquidity using the i) absolute CDS bid-ask spread, ii) the number of contributors that provide quotes to Markit for 5 year CDS spreads, iii) the gamma measure of CDS illiquidity similar to the gamma measure of bond illiquidity of Bao et al. (2011), iv) the return-to-volume measure of CDS illiquidity similar to the illiquidity measure of Amihud (2002) for stocks and v) the Fitch liquidity score.

Bid-ask spread is one of the most widely used measures of liquidity in finance. This variable provides a measure of the tightness of the CDS market. According to the literature, bid-ask spread reflects order processing, inventory holding and information asymmetry costs (see Venkatesh and Chiang (1986), Stoll (1989) or Krinsky and Lee (1996), among others). We construct the absolute bid-ask measure of illiquidity for a CDS on a monthly basis. More specifically, we proceed by taking the last non-missing bid-ask spread for each month. We consider absolute or quoted rather than relative bid-ask spread. Pires et al. (2010) and Coro et al. (2012) argue that absolute bid-ask spread is already a proportional measure, hence there is no need to scale it by the average of CDS ask and bid quotes. As liquidity dries up, the size of bid-ask spread increases.

Hence, we expect a positive relationship between changes in CDS spreads and changes in the bid-ask spread. Our sample of bid-ask spreads is composed of daily spreads for 5-year maturity CDS names and its taken from CMA Datastream. The data is available from January 1, 2004.

We consider the number of contributors (NOC) that submit to Markit the 5-year CDS quotes as another proxy for CDS illiquidity. Those contributors are usually big commercial and investment banks actively trading in CDS contracts. Hence their concentration could reflect the degree of competitiveness in CDS markets. Less competitive markets can lead to reduced liquidity provisions. With the NOC measure we try to capture the aspect of CDS liquidity that is associated with the size and competitiveness of CDS markets. A positive change in NOC might be interpreted as a sign of growing interest by market participants in buying or selling credit protection for a particular CDS. Consequently, positive changes in NOC can be attributed to increased liquidity in CDS markets for a given CDS name, which should be associated with a drop in the price for credit protection. In this context, we expect to find a negative relationship between changes in NOC and changes in CDS spreads. We take the last non-missing number of contributors for each CDS name and month to construct the individual NOC series. Data on NOC has also been obtained from Markit.

The market depth measures the impact of a trade on the security price. An asset is considered to be liquid if a large amount of the security can be traded without affecting its price. Since CDS contracts are not traded in an organized markets and the data on the CDS trading volumes is not available to us, we construct an illiquidity proxy similar to the stock illiquidity measure of Amihud (2002) to account for the depth of the CDS market,

$$ILRTV_t^i = \frac{1}{N_{t,d}} \sum_{d=1}^{N_{t,d}} \frac{|r_{t,d}^{cds5y}|}{NOC5y_{t,d}}$$

where $N_{t,d}$ is the number of days in month t for which data is available for CDS name i, $r_{t,d}^{cds5y}$ is the daily return on a CDS contract with 5-year maturity for day d in month t, and $NOC5y_{t,d}$ is the number of market contributors providing quotes to Markit for a 5-year CDS spread at day d in month t. To construct the CDS returns we closely follow the methodology of Berndt and Obreja (2010).

One might argue the fact that we approximate the trading volume of CDS contracts by the number of market contributors. Although this may not be true, the OTC nature of CDS markets leads us to introduce additional assumptions. We believe that NOC could proxy quite closely the amount of trading activity of a

CDS contract because it might indicate that, at least, NOC number of trades could have been executed for a CDS name for a given day.

Our fourth proxy is the gamma measure of CDS illiquidity similar to the gamma measure of bond illiquidity of Bao et al. (2011),

$$ILCDSCOV \quad = \quad Cov(r_t^{cds}, r_{t+1}^{cds})$$

where r_t stands for the CDS return. This formulation of gamma illiquidity slightly modifies the one employed by Bao et al. (2011), which is defined as the *negative* covariance between consecutive bond price changes. The reason for the negative sign is due to the fact that bond price returns exhibit negative serial correlation (see Roll, 1984). However, CDS returns approximate by construction the yield changes of the underlying bond (see, for instance, Berndt and Obreja (2010)). The reason is that CDS spreads are approximately equal to the bond yield minus the risk free rate (e.g., see Blanco et al. (2005), Hull et al., 2004). As it is known, bond yield changes and bond returns are inversely related.

Finally, we consider a synthetic CDS illiquidity measure provided by Fitch. It is known as Fitch liquidity score. This variable is a composite measure which incorporates several aspects of CDS liquidity such as the bid-ask spread levels, the dispersion of mid-quotes across brokers, and the number of market participants. The documentation provided by Fitch suggests that this measure should be interpreted as a pure measure of liquidity because it controls for the default risk of the underlying CDS name. According to the documentation on the liquidity score, the lower the score, the higher the liquidity of the corresponding CDS name.

Figure 3 displays the time series of our liquidity proxies by rating group. The time series of each measure is constructed by taking the cross-sectional averages of the corresponding measures for each month and rating group. Liquidity variables are bid-ask spreads (upper left graph), number of contributors (upper right), return to volume (medium left), gamma measure (medium right) and Fitch liquidity scores (bottom). In general, the variables exhibit the expected behavior: bid-ask spreads widen and the NOC decreases during the period of the crisis. The return to volume and gamma measures also increase substantially after August 2007. The only exception in this respect is the Fitch liquidity score, which suggests that illiquidity decreases after August 2007.

[INSERT FIGURE 3 ABOUT HERE]

An interesting feature of Figure 3 is the rating effect in the liquidity variables. Bid-ask spreads, return to volume and gamma measures clearly connect lower ratings with higher illiquidity. These results seem to be consistent as rating improves. On the contrary, we do not observe such a direct interpretation for NOC or Fitch liquidity scores.

Table 3 presents the summary statistics for 5-year CDS liquidity measures. We observe that the average bid-ask spread is around 20 basis points (bps), exhibiting a high standard deviation (67.78 bps) for the entire sample. The average number of contributors is 10. This variable shows a low fluctuation (4.20), with a maximum of 16 contributors in the 95% of the sample. Gamma and volume measures present higher deviations, where extreme values are common. Lastly, the Fitch score seems to be a very stable measure: it has a mean score of 8.26, displaying a low variation (1.03 standard deviation) in an interval that ranges from 6.85 to 10.02 in the 10th to 90th percentile range.

[INSERT TABLE 3 ABOUT HERE]

Table 4 provides the correlation matrix between liquidity variables. The correlation among the liquidity proxies is generally small with the exception of return-to-volume measure. This variable has a relatively high correlation (0.58) with bid-ask spread, and -0.23 and -0.35 with number of contributor and gamma illiquidity, respectively. The low correlation levels among other variables might suggest that the dependence between those variables is not linear.

[INSERT TABLE 4 ABOUT HERE]

3.2 Determinants of CDS liquidity

To understand why some CDS contracts are more liquid than the others, we run a panel data regression of our liquidity measures on company specific variables. For this reason we consider the following company specific control variables i) the 1-year expected default frequency (EDF1y), an estimate of the actual default probability of the firm, ii) the realized volatility (RVOL) of the stock returns of the underlying CDS company, iii) the market capitalization (ME) in logs and iv) the composite monthly rating (RATING) constructed by averaging credit ratings of S&P, Fitch and Moody's.

Table 5 provides the results of panel regressions of liquidity proxies on firm specific variables and monthly dummies. We observe that higher default probabilities and realized stock return volatility are associated with higher bid-ask spreads, return-to-volume and Fitch score measures, respectively. In other words, when the companies become riskier, the liquidity associated with their corresponding CDS spreads increases. When the market capitalization of the underlying CDS names increases, the liquidity of CDS spreads (as measured by bid-ask spread, gamma illiquidity, return-to-volume) improves. As for the ratings, when the credit quality of the underlying CDS names deteriorates or increases (1 corresponds to AAA, 2 to AA+, 21 to D), bid-ask spread and return-to-volume increases. This is consistent with the results on default probabilities and realized stock return volatility described above. Finally, the results are counter-intuitive for the number of contributors and Fitch liquidity score.

[INSERT TABLE 5 ABOUT HERE]

4 Liquidity and CDS spreads

This section analyzes the relationship between our liquidity proxies and default swap spreads using panel data regressions. We also control for a set of variables previously employed in the literature.

4.1 Control Variables

In addition to the liquidity proxies, we control for several factors associated with the creditworthiness of the underlying CDS names. We partially follow Collin-Dufresne et al. (2001) when choosing a set of control variables associated with credit risk of the CDS names. The variables that we choose are as follows:

1. The expected default frequency (EDF) is a measure of the actual probability of default for a given firm over a specified period of time. We use EDF with 1 year maturity in our regression analysis. EDF data has been previously analyzed in Bharath and Shumway (2008). It has been also employed for backing out the default event risk premium embedded in excess bond yields or CDS spreads (see Berndt et al., 2008).

2. As we do not have access to implied volatilities, instead we use the realized volatilities of stock returns. We calculate the realized volatilities of stock returns by taking the standard deviation of stock returns using a 30-day window.

3. Return on market capitalization. In structural default models, default happens when the leverage ratio gets close to one. Similarly, CDS spreads should be a decreasing function of the firm's return on equity all else being equal. Hence, instead of changes in the leverage ratio, we employ equity returns of a CDS reference entity. We use the data on monthly equity returns downloaded from CRSP.

4. Volatility. We use the changes in the VIX index as a global indicator of market volatility. It has been employed in other studies such as Pan and Singleton (2008).

5. Changes in the slope of the yield curve. The spot interest rate is the only interest rate that is relevant for the determination of the firm value process in structural models. However, the spot rate can itself depend on other factors, such as the slope of its term structure. The slope of the term structure (of interest rates) is constructed by taking the difference between 10 year and 3 month bond yields (end of month) of US Treasury bonds and yields, respectively. The data in downloaded from Datastream.

6. Changes in Moody's bond yield index spread, where the spread is defined as the difference between Moody's Aaa and Baa bond yield index levels.

Table 6 provides the summary statistics of our liquidity proxies and control variables employed in this article. We also report some previous references (if available) that have employed these variables.

[INSERT TABLE 6 ABOUT HERE]

4.2 The effect of liquidity on CDS spreads

To assess the relationship between our liquidity proxies and CDS spreads, we estimate the following panel data model using fixed effects,

$$\begin{aligned}\Delta CDS_{i,t} &= \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} \\ &+ \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $CDS_{i,t}$ is the 5-year CDS spread of name i for month t, $ILBAS5y$ is the quoted bid-ask spread, $NOC5y$ is the number of contributors, $ILCOV5y$ is the gamma measure of illiquidity of 5-year CDS contract, $ILRTV5y$ is the return-to-volume measure, and $LSCORE$ is the Fitch's liquidity score. $Control_{i,t}$ is the vector of control variables, which includes Moody's EDF measure of default probabilities, realized stock return volatility, return on equity of the underlying CDS name, the VIX index, the slope of the term structure of interest rates, and the spread of Moody's Aaa and Baa bond yield indices.

Table 7 reports the regression results of model (12). To stress the effects of financial crisis, we repeat the estimations for our data before and after August 2007. Robust standard errors are adjusted for issuer-clustering. Since we employ macroeconomic variables in our panel data analysis, model (12) does not include time dummies. Results in Table 7 are strong: illiquidity is a significant determinant in explaining CDS spreads. This result seem to be consistent across different measures of liquidity. More specifically, panel estimates reveal that the bid-ask spread is a significant determinant of 5-year CDS spreads. The sign of the bid-ask spread variable is positive and its magnitude increases after August 2007.

[INSERT TABLE 7 ABOUT HERE]

With regard to the gamma and return-to-volume measures, Table 7 shows that their beta coefficients are positive and statistically significant (as illiquidity increases CDS spreads go up). Even though the magnitude of the coefficients of those variables falls during the crisis, they still remain statistically significant.

The regression results of number of contributors (NOC) and Fitch liquidity score seem to be counter-intuitive. For example, changes in NOC is a significant factor for explaining changes in CDS spreads. Contrary to our conjecture, the sign of NOC is positive. Fitch liquidity score also suggests similar results: liquidity improves as credit environment deteriorates. These results still puzzle us.

Finally, the control variables included in our analysis are significant factors for explaining CDS spreads. As expected, an increase in company specific variables such as EDF and realized volatility lead to high CDS spreads; and a decrease in equity returns also results in higher CDS spreads. Global variables such as the VIX index, the slope of the term structure (of interest rates) and Moody's Aaa-Baa spread are also significant factors for CDS spreads with the expected sign for both time periods.

5 The constituents of CDS spreads

We analyze whether liquidity is priced by default swap investors. We decompose CDS spreads into their risk premium and default risk components. This section introduces the methodology of Pan and Singleton (2008), and it also presents our estimation results.

5.1 The model

The intensity modeling framework has it roots in Duffie and Singleton (1999) and Lando (1998). Within this methodology, the default event is specified as the first jump of a Poisson process, where the intensity of the process evolves stochastically in time. The survival probability p of a firm is given by

$$p(t,T) = E\left[e^{-\int_t^T \lambda_s ds}\right], \tag{3}$$

where λ is the stochastic intensity of the Poisson process. This formulation permits us to compute the expectations in equation (1) using the same machinery used for models of the term structure of interest rates (Duffie et al., 2000).

Since default and liquidity are not easily discernible events, we hypothesize that the intensity process accounts for both default and liquidity factors as in Longstaff (2011). Thus, the dynamics of the default/liquidity process λ_t^Q under the physical measure P is given as a Black and Karasinski (1991) process, where the logarithm of the state variable follows an Ornstein-Uhlenbeck (logOU) process,

$$d\ln\lambda_t^Q = \kappa^P(\theta^P - \ln\lambda_t^Q)dt + \sigma dW_t^P, \tag{4}$$

and κ^P and θ^P are the actual mean-reversion speed and long-run mean, respectively, and σ accounts for the volatility of the process. The logOU process allows for mean reversion and it ensures the positiveness of the default intensity. This specification has been previously employed by Pan and Singleton (2008) and Longstaff et al. (2011).

To price a CDS, we need to specify the process (4) under the risk neutral measure Q. The change of measure from P to Q implies that

$$d\ln\lambda_t^Q = \kappa^Q\left(\theta^Q - \ln\lambda_t^Q\right)dt + \sigma dW_t^Q, \tag{5}$$

where $\kappa^Q = \kappa^P + \delta_1\sigma$ and $\kappa^Q\theta^Q = \kappa^P\theta^P - \delta_0\sigma$. Additionally, parameters δ_0 and δ_1 are governing the market price of risk η, where

$$\begin{aligned} dW^Q &= \eta dt + dW^P \\ &= \left(\delta_0 + \delta_1 \ln \lambda^Q\right) dt + dW^P. \end{aligned}$$

The market price of risk allows the mean reversion rate of $\ln \lambda^Q$ to be different under the P and Q measures. Moreover, the dynamics of the default intensity can differ under both measures. Finally, note that we specify the risk neutral default intensity process λ^Q under two different measures. The default intensity under the historical measure λ^P does not play any role in our analysis.

5.2 Risk premium

Jarrow et al. (2005) describe the two types of risk premia in underlying CDS bonds. The first type of risk premia designates the compensation associated with the unpredictable variation in the arrival rate of a credit event of the bond issuer. This type of risk premia is also known as *distress* premium, and it has been estimated by Pan and Singleton (2008) or Longstaff et al., 2011 for sovereign CDS spreads. The other type type of risk premia, also known as *jump-at-event* premium, denominates the compensation associated with the default event itself. Jump-at-event risk premium has been analyzed by Pan and Singleton (2006) and Berndt et al. (2008), among others.

We focus on the distress risk premium in corporate default swaps, similarly to Pan and Singleton (2008) and Longstaff et al. (2011) for sovereign CDS markets. To quantify the risk premium embedded in CDS spreads, we first compute CDS spreads using the risk neutral parameter values of λ^Q by means of equation (1) and (5). By restricting the parameter of the market price of risk to be zero ($\delta_0 = \delta_1 = 0$), we are able to calculate a *pseudo* CDS spread under the physical measure,

$$CDS_t^P(M) = \frac{4L^{\mathbb{Q}} \int_t^{t+M} E_t^{\mathbb{P}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u (r_s + \lambda_s^{\mathbb{Q}})\, ds} \right] du}{\sum_{i=1}^{4M} E_t^{\mathbb{P}} \left[e^{-\int_t^{t+.25i} (r_s + \lambda_s^{\mathbb{Q}})\, ds} \right]} \quad , \tag{6}$$

where the default intensity is given by (4).

Note that if the market price of risk η_t is zero, then the risk neutral and objective intensity of λ^Q will be the same. This then implies that $CDS^Q = CDS^P$. However, if η_t is not zero, the parameters of the λ^Q process under both measures will differ. Hence, CDS spreads calculated under P and Q measures will be different. By subtracting CDS^P from CDS^Q we obtain an estimate of the distress default premium, which we denote by RP.

5.3 Econometric Framework

We closely follow Pan and Singleton (2008) and Longstaff et al. (2011) to estimate the parameters of the process via Maximum Likelihood (ML). This technique has been also employed by Duffie and Singleton (1997) and Duffie et al. (2003) with CIR-type models. For ease of notation, we denote λ^Q as λ. To identify the λ process and its parameters, we employ the full CDS spread term structure available to us. It comprises default swap spreads with 1-, 3-, 5-, 7- and 10-year maturities. We bootstrap the daily term structure of risk-free interest rates from USD Libor and IRS swap rates. More specifically, we use the 3-, 6-, 9- and 12-month USD Libor rates that are published by the British Bankers' Association, and the 2-, 3-, 4- and 5-year USD interest rate swaps from the Federal Reserve Statistical Release H.15.

To explain our estimation procedure, we first assume that 5-year CDS contracts are priced without error. Then, we extract the λ_t time series inverting the pricing function (1):

$$\lambda_t = f^{-1}(CDS_t(5); \kappa^Q, \theta^Q, \sigma). \tag{7}$$

Second, we denote $CDS_t(M)$ as the remaining observed default swap spreads with maturities $M = 1,3,7$ and 10 years, respectively. Those contracts are assumed to be measured with normally distributed errors $\varepsilon_t(M)$, with zero means and standard deviations $\sigma_\varepsilon(M)$. For simplicity, those errors are uncorrelated across maturities and not autocorrelated individually,

$$\varepsilon_t(M) = CDS_t(M) - CDS_t^Q(M) \sim N\left(0, \sigma_\varepsilon^2(M)\right), \quad M = 1,3,7,10 \tag{8}$$

with $CDS_t^Q(M)$ the theoretical spread using equation (1) and the implied λ_t values from the first step.

Third, the probability function of the intensity process also plays a role in the estimation procedure of the log normal model. Since the logarithm of λ follows a log-OU process, its density $f^P(\ln\lambda | \kappa^P, \theta^P, \sigma)$ is the likelihood function of a Gaussian AR(1) process with parameters κ^P, θ^P and σ under the objective measure.

Finally, the last step consists of maximizing the joint likelihood function,

$$f^P(\Theta,\lambda) = f^P(\overline{\varepsilon}|\sigma(M)) \times f^P(\ln\lambda|\kappa^P,\theta^P,\sigma) \times \left|\partial CDS^Q(\lambda|\kappa^Q,\theta^Q,\sigma)/\partial\lambda\right|^{-1} \tag{9}$$

where $\overline{\varepsilon}$ denotes the vector of misspricing errors, $\left|\partial CDS^Q(\cdot)/\partial\lambda\right|$ the corresponding Jacobian of the transformation and the parameter vector is $\Theta = (\kappa^Q, \kappa^Q\theta^Q, \kappa^P, \sigma, \sigma_\varepsilon(1), \sigma_\varepsilon(3), \sigma_\varepsilon(7), \sigma_\varepsilon(10))$. Finally, Δt is fixed, and it is equal to $1/12$ because of the monthly frequency of our data.

5.4 Estimation results

Table 8 summarizes the results of the ML estimation[8]. We find significant differences between the parameters estimated under P and Q measures. On median, the mean-reversion rate under risk-neutral measure (κ^Q) is lower than the objective measure (κ^P), implying that the risk-neutral environment worsens as time goes by. Additionally, the default arrival rate is much higher under Q than P measure as inferred from $\kappa^Q\theta^Q > \kappa^P\theta^P$. Those two observations suggest that a systematic risk premium is priced in the CDS market that is associated with the unpredictable variation in the arrival rate of a credit event (Pan and Singleton, 2008).

[INSERT TABLE 8 ABOUT HERE]

The magnitude of CDS spread misspricing for maturities other than 5 years can be judged by the $\sigma_\varepsilon(M)$ parameters for $M = 1,3,7,10$. The results show that misspricing is highest for shorter maturities, particularly 1-year maturity. On average, $\sigma_\varepsilon(1)$ is 89.22 basis points, and 27.33 in median. This pattern seems to be consistent when comparing with the distribution of misspricing volatilities to other maturities (e.g. percentile 95%).

To further assess the scale of misspricing of the log normal model, Figure 4 plots the cross-sectional, averaged time series of relative misspricing of logOU model by maturity. Relative misspricing is defined as $(CDS(M) - CDS^Q(M))/CDS^Q(M)$, where $CDS(M)$ is the market observed CDS spread with M year maturity, and $CDS^Q(M)$ is the model implied CDS spread. Figure 4 clearly shows the high level of misspricing of 1-year maturity CDS spreads, especially when it is compared with other maturities. In terms of numbers, the

[8] The detailed list of the ML estimates for the firms under study is provided in the Appendix A.

average (median) misspricing for 1-year CDS is -14.46%(-4.67%), against -5.84%(-5.03%), -2.71% (-2.05%) and -1.99%(0.31%) for 3, 7 and 10-year maturities, respectively.

[INSERT FIGURE 4 ABOUT HERE]

Table 9 provides the summary statistics for the 5-year distress risk premium when grouping the firms by Rating (Panel A) and Sector (Panel B), respectively. The absolute risk premium is defined as the difference between CDS model implied spreads using expressions (1) and (4). We also report the relative distress risk premium (DRP) measure:

$$DRP(M) = (CDS^{Q}(M) - CDS^{P}(M))/CDS^{Q}(M). \tag{10}$$

This measure quantifies the percentage of risk premium embedded in CDS spreads, similarly to Longstaff et al. (2011).

[INSERT TABLE 9 ABOUT HERE]

According to Panel A in Table 9, the market demands higher risk premia (on average) from lower-rated firms. Risk premium ranges from 22.24 bps for AA-rated companies to 254.09 bps for B-rated companies. The standard deviation of the premium also increases as the credit quality worsens. Additionally, the distress compensation does not seem to follow a linear pattern. An investor moving from BB to B rating category (non-investment grade) demands 118.46 bps additionally for selling protection, versus 8.94 bps when going from AA to A. In terms of their relative contribution, risk premium represents around 28% (42%) of the total AA(B)-rated firm CDS spread[9].

When grouping the risk premium by sectors, Panel B in Table 9 shows that lower risk premia is observed for Telecommunications and Industrial sectors with 81.96 and 85.65 bps, respectively. On the other hand, maximum risk premia (on average) is demanded for Technology (141.82 bps) and Consumer Services (136.91 bps). Surprisingly enough, the relative contribution of risk premium by sectors is (on average) around 40%, with the sole exception of 11% for Financials.

Lastly, Figure 5 depicts the averaged cross-sectional time series of relative risk premium by maturity. Taking the 5-year maturity as a base, we can observe that risk premium increases substantially from around

[9]The conflicting result in rating CCC might be due to the scarcity of these firms, which represent a 6.3% of our total sample.

30% before the crisis to almost 60% after August 2007. According to these results, the financial crisis has resulted in a generalized increase in the level of risk premia.

[INSERT FIGURE 5 ABOUT HERE]

6 The effects of liquidity on CDS constituents

This section examines the relationship between CDS components and the liquidity proxies of our study. More specifically, we analyze the influence of liquidity on risk premium and default risk constituents of default swap spreads.

To explore these questions, we first project the individual CDS risk premium on a set of variables,

$$\begin{aligned} \Delta RP_{i,t} &= \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} \\ &+ \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where $RP_{i,t}$ is the 5-year risk premium of name i for month t, $ILBAS5y$ the bid-ask spread, $NOC5y$ is number of contributors, $ILCOV5y$ the gamma measure of 5-year CDS contract, $ILRTV5y$ the return-to-volume measure and $LSCORE$ the Fitch's liquidity score. Finally, $Control_{i,t}$ is the vector of variables previously introduced in subsection 4.1.

Table 10 provides the results for the CDS risk premia. We observe that our liquidity measures are significant determinants of CDS risk premia. These results are robust for different subsamples. When considering the liquidity variables individually, we find that higher bid-ask spreads, gamma and return-to-volume proxies lead to higher risk premium. In other words, as liquidity dries up, protection sellers ask for higher compensation for providing credit protection. As in case of CDS spreads, the number of contributors (NOC) and Fitch liquidity scores produce results that are contrary to our expectations. More specifically, we find that higher number of contributors and Fitch liquidity score are associated with higher and lower risk premia, respectively. At this point it is worth mentioning that low Fitch liquidity score corresponds to higher liquidity of the corresponding CDS name. Hence, these results are counter-intuitive and raise some concerns of whether NOC (or functions of NOC) is a true proxy for liquidity.

[INSERT TABLE 10 ABOUT HERE]

Table 11 estimates the panel regressions of CDS default risk component according to the following model,

$$\begin{aligned} \Delta CDS^{P}_{i,t} &= \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} \\ &+ \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{12}$$

where $CDS^{P}_{i,t}$ is the 5-year default risk component of name i for month t. According to Table 11, liquidity variables have a significant effect on CDS default risk component. Interestingly, only bid-ask spreads, gamma and return-to volume measures are significant factors for explaining the default part of CDS (NOC is also significant at 10% level). The positive sign of the coefficients of bid-ask spreads, gamma and return-to-volume measures indicate that higher illiquidity leads to higher default component of CDS spreads. Since the point estimates of the number of contributors and Fitch liquidity score variable are not significant when considering different subsamples, it suggests that the presence/absence of contributors does not affects the default component of CDS spreads. Changes in control variables have a significant effect with the expected coefficient signs on the CDS default component.

[INSERT TABLE 11 ABOUT HERE]

In conclusion, previous results suggest that illiquidity is an important determinant that can explain the risk premium of default swap spreads. Additionally, illiquidity also matters for the default risk component of CDS spreads. Finally, number-of-contributors and Fitch liquidity score measures exhibit unexpected results. Since the usefulness of number of contributors and Fitch liquidity score variables on capturing illiquidity is not well studied in the literature, these results should be interpreted with caution.

7 Conclusions

Default swap markets nowadays play a leading role in assessing the default risk of firms and institutions. However, the interaction between liquidity supply and CDS markets can distort the information content of default swaps spreads. This article analyzes the relationship between illiquidity and CDS spreads.

To explore this question, we approximate liquidity by the CDS bid-ask spreads and the number of contributors. We also introduce additional measures for liquidity such as the gamma measure of Bao et al. (2011), the return-to-volume ratio of Amihud (Amihud, 2002) and the Fitch liquidity score. Then, we conduct our analysis in two steps. First, we run panel data regressions to study the relationship between our liquidity measures and plain CDS spreads. Second, we separate CDS spreads into risk premium and default risk component using the decomposition technique of Pan and Singleton (2008). Finally, we analyze the relationship of CDS spread constituents with the proposed liquidity proxies.

Our findings reveal that changes in bid-ask spreads, gamma and return-to-volume measures have a significant effect on changes in CDS spreads during the period of 2004-2011. Moreover, illiquidity proxied by bid-ask spreads intensifies as the credit crisis worsens. Changes in the number of contributors and the Fitch liquidity score have a significant effect on changes in CDS spreads. However the sign of the coefficients of those variables are counter-intuitive, which are still puzzling us.

In our analysis of the risk premium, our estimation results show considerable differences in the estimated parameters for credit event arrival rates under P and Q measures. Our results suggest that an important fraction of CDS spreads associated with uncertainty over the future credit risk environment is systematically being priced via the distress risk premium. According to our results, risk premium ranges from 22.24 bps for AA-rated companies to 254.09 bps for B-rated companies. In terms of their relative contribution, risk premium represents around 28% (42%) of the total CDS spreads of AA(B)-rated firms. When controlling by sectors, we document a relative contribution of risk premium (on average) around 40%, with the sole exception of 10% for Financials.

Our panel data regressions on risk premium and default risk CDS components show a significant interaction between CDS constituent and our liquidity proxies. Again, the results for the number of contributors and Fitch score are still puzzling us.

In conclusion, our results suggest that illiquidity constitutes an important factor for explaining the CDS spreads. These results hold for risk premium and default risk components of CDS spreads. Finally, the number of contributors and Fitch liquidity score exhibit opposite effects.

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Table 1: Distribution of CDS names by Sector and Rating

	AA	A	BBB	BB	B	CCC	Total
Basic Materials		1	7	6	2		16
Consumer Goods		1	13	12	1	5	41
Consumer Services	1	6	29	14	2	2	72
Financials	3	11	9	8	4	8	43
Health Care	1	6	2	3	2		14
Industrials	1	5	16	6	4		32
Oil & Gas		4	6	8	1		19
Technology		6	5	3	4		18
Telecommunications		7	2	4		1	14
Utilities		1	5	3	3	2	14
Total	6	48	94	67	5	18	283

This table shows the sample distribution of CDS names by rating and ICB Industry category. Ratings correspond to the averaged Moody's and S&P grades adjusted by instrument seniority.

Table 2: Summary Statistics of CDS spreads

	mean	sd	min	5%	med	95%	max	N
AA								
1y	42.63	101.62	1.06	1.66	11.38	157.61	950.53	455
3y	51.37	95.20	1.54	3.33	21.29	186.54	811.87	455
5y	59.64	90.75	2.94	5.32	30.53	195.57	737.96	455
7y	61.91	83.84	4.68	8.02	34.38	198.35	680.53	455
10y	65.57	79.42	5.05	10.81	39.12	199.26	652.67	455
A								
1y	40.32	163.78	1.36	2.98	13.82	126.20	6524.64	3839
3y	51.14	133.74	3.89	6.88	24.70	153.83	4391.16	3845
5y	62.69	119.67	6.93	12.04	36.97	175.59	3606.86	3846
7y	67.80	107.83	10.08	17.35	44.25	179.60	3132.83	3845
10y	74.08	98.44	12.87	22.98	52.62	184.24	2714.45	3845
BBB								
1y	74.81	283.47	1.78	4.78	22.36	249.70	10594.97	7425
3y	90.34	229.03	4.51	12.45	41.08	277.24	7820.38	7428
5y	107.22	206.55	8.59	21.86	60.39	290.75	7053.63	7432
7y	113.35	186.03	12.80	29.78	70.85	287.21	6069.29	7407
10y	120.97	169.08	17.20	37.86	82.33	291.55	5416.57	7396
BB								
1y	181.62	415.94	1.29	10.42	75.72	629.74	10376.70	4385
3y	239.34	380.37	8.76	25.66	141.28	699.85	7330.14	4389
5y	281.67	354.45	14.96	41.61	191.24	718.24	6347.23	4419
7y	289.55	328.14	19.96	49.90	208.20	693.10	5780.23	4385
10y	296.81	304.71	22.95	58.81	225.28	678.40	5283.29	4377
B								
1y	415.22	883.27	4.36	14.60	168.65	1491.53	12686.53	3873
3y	514.30	760.37	7.42	31.73	308.73	1562.04	11246.86	3893
5y	573.08	689.49	14.06	52.12	409.10	1516.38	11762.57	3914
7y	573.01	631.28	17.96	65.46	437.77	1414.15	11397.80	3873
10y	567.13	569.05	26.36	77.35	459.40	1303.85	9235.43	3862
CCC								
1y	1310.41	3155.83	5.14	14.66	397.38	5621.31	35045.89	1154
3y	1263.96	2471.88	12.51	27.96	570.55	4807.91	36934.43	1157
5y	1221.95	2115.54	20.26	42.51	647.73	4248.77	27913.98	1162
7y	1166.30	1933.11	24.78	49.90	664.92	4072.41	24371.56	1153
10y	1099.39	1735.99	31.47	59.45	667.61	3632.74	22493.20	1156
Total								
1y	219.89	917.50	1.06	4.54	40.93	776.84	35045.89	21131
3y	255.40	760.19	1.54	11.02	72.45	924.98	36934.43	21167
5y	281.36	678.77	2.94	18.89	102.00	972.67	27913.98	21228
7y	282.32	625.54	4.68	25.75	113.24	933.71	24371.56	21118
10y	283.04	570.14	5.05	32.93	124.13	888.41	22493.20	21091

Summary statistics of pooled CDS spreads by rating group and maturity. Spreads are in basis points (bps). The sample frequency is monthly and it spans from January 2004 to April 2011.

Table 3: Summary Statistics of CDS Liquidity Measures

	ILBAS5y	NOC5y	ILCOV5y	ILRTV5y	LSCORE
mean	19.97	8.57	0.47	4.76	8.26
sd	67.78	4.20	159.22	12.04	1.03
min	0.00	2.00	-7167.53	0.01	5.09
p5	3.00	3.00	-2.73	0.10	6.85
p50	9.46	8.00	0.10	1.68	8.14
p95	58.00	16.00	25.20	17.61	10.02
max	2724.00	27.00	3722.25	393.20	17.69

Summary statistics of our liquidity proxies computed for 5-year CDS spreads. ILBASS stands for the bid-ask spreads. NOC is the number of contributors. ILCOV represents the gamma measure of illiquidity. ILRTV and LSCORE are the return-to-volume and Fitch liquidity score variables, respectively.

Table 4: Correlation Matrix of Liquidity Measures

Panel A: In Levels:

	ILBAS5y	NOC5y	ILCOV5y	ILRTV5y	LSCORE
ILBAS5y	1				
NOC5y	-0.114	1			
ILCOV5y	-0.0593	0.0224	1		
ILRTV5y	0.576	-0.234	-0.357	1	
LSCORE	0.0335	0.0296	-0.0794	-0.0210	1

Panel A: In Differences:

	ΔILBAS5y	ΔNOC5y	ΔILCOV5y	ΔILRTV5y	ΔLSCORE
ΔILBAS5y	1				
ΔNOC5y	-0.0129	1			
ΔILCOV5y	-0.0204	0.00791	1		
ΔILRTV5y	0.121	-0.0118	-0.577	1	
ΔLSCORE	0.0437	-0.165	-0.0856	0.0870	1

Table 5: CDS Liquidity Determinants

	ILBAS5y		NOC5y		ILCOV5y		ILRTV5y		LSCORE	
EDF1y	0.97***	(6.76)	0.23***	(3.11)	0.16**	(2.61)	0.21***	(2.95)	0.07***	(2.67)
RVOL	1.02***	(7.12)	0.19*	(1.87)	0.50***	(9.46)	0.52***	(9.95)	-0.04**	(-2.15)
ME	-1.46***	(-3.36)	-0.53	(-1.13)	-0.87***	(-5.53)	-0.63***	(-3.33)	0.32***	(2.89)
RATING	0.30*	(1.84)	-0.26	(-1.36)	0.03	(0.69)	0.22***	(3.12)	-0.02	(-0.48)
Cons	27.49***	(3.76)	20.48**	(2.53)	13.01***	(4.79)	8.76**	(2.57)	4.45**	(2.17)
monthly dummy	Yes		Yes		Yes		Yes		Yes	
N	7723		9224		8818		8562		5534	
adj. R^2	0.388		0.494		0.261		0.480		0.489	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results of panel regressions of liquidity proxies on firm control variables and monthly dummies. $EDF1y$ is the expected default frequency of the underlying CDS name over 1 year horizon. $RVOL$ is the realized volatility of the stock returns of the underlying CDS name. ME is the log of market capitalization of the underlying CDS name. Finally, $RATING$ is the composite monthly rating of a CDS name constructed by averaging credit ratings of S&P, Fitch and Moody's.

Table 6: Variable definitions

Name	Definition	References
	Panel A.- Liquidity Variables	
ILBAS5y	The quoted bis-ask spread of a 5 year CDS contract (end of month value).	Tang and Yan (2010), Venkatesh and Chiang (1986), Stoll (1989), Krinsky and Lee (1996)
ILCOV5y	The gamma measure of iliquidity of a 5 year CDS contract.	Bao et al. (2011)
ILRTV5y	The return-to-volume measure of iliquidity of a 5 year CDS contract.	Amihud (2002)
$r_t^{cds}(M)$	Return on a CDS contract with M year maturity.	Berndt and Obreja (2010), Bongaerts et al. (2011)
	Panel B.- Company Specific Control Variables	
EDF1y	Expected Default Frequency of the underlying CDS company over 1 year horizon.	**?**
ME	Market capitalization of underlying CDS name (end of month level).	
RETEQ	Return on equity of underlying CDS name: $((ME_t - ME_{t-1})/ME_{t-1})$.	
RVOL	The realized volatility of the stock returns of underlying CDS name (calculated over daily observations within each month and company).	
	Panel C.- Macroeconomic Variables	
VIX	The VIX index (end of month value).	Pan and Singleton (2008)
SLOPE	The difference between 10-year Treasury bond and 3-month Treasury bill yields (end of month value).	
DEF	The difference between the Moody's Aaa and Baa bond yield index levels (end of month value).	Longstaff et al. (2008)

Summary of liquidity and control variables. Displayed references provide a detailed description of the variable or use a similar measure in their empirical research. Data sources are Markit, Datastream, Thomson Reuters and Yahoo Finance.

Table 7: Panel Data Analysis for CDS spreads

This table reports the results for the panel data regression,

$$\Delta CDS_{i,t} \quad = \quad \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} + \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t}$$

where $CDS_{i,t}$ is the 5-year CDS spread of name i for month t, $ILBAS5y$ their quoted bid-ask spread, $NOC5y$ is number of contributors, $ILCOV5y$ the gamma measure of 5-year CDS contract, $ILRTV5y$ the return-to-volume measure and $LSCORE$ the Fitch's liquidity score. Finally, variable $Control_{i,t}$ is the vector of control variables which includes firm specific and global variables. Firm specific variables are the expected default frequency ($EDF1y$), the realized volatility of the stock returns ($RVOL$), the return on equity ($EQRET$) and the log of market capitalization (ME) of the underlying CDS names, respectively. The global variables considered are the VIX index (VIX), the slope of the interest rate curve ($SLOPE$) measured as the difference between 10-year Treasury bond and 3-month treasury bill yields and the difference between Moody's Aaa and Baa bond yield indexes (DEF). The model is estimated with issuer fixed effect. Robust standard errors are adjusted for issuer-clustering.

	01/2004 to 04/2011					01/2004 to 06/2007					06/2007 to 04/2011				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Δ ILBAS5y	2.18***					1.74***					2.76***				
	(11.90)					(9.52)					(7.33)				
Δ NOC5y		0.39***					0.19**					0.75***			
		(4.14)					(2.11)					(3.54)			
Δ ILCOV5y			2.38***					4.07***					1.56***		
			(6.73)					(5.07)					(4.55)		
Δ ILRTV5y				4.33***					6.55***					2.19**	
				(6.16)					(6.78)					(2.23)	
Δ LSCORE					−8.39***					−5.33*					−7.63***
					(−5.03)					(−1.71)					(−4.91)
Δ EDF1y	14.76***	15.25***	16.83***	15.82***	6.79***	28.71***	28.61***	24.81***	24.23***	19.00	6.16*	5.42**	8.89**	9.75***	5.29**
	(3.42)	(4.13)	(4.84)	(3.80)	(2.90)	(3.50)	(3.74)	(3.50)	(2.96)	(1.09)	(1.96)	(2.02)	(2.27)	(3.11)	(1.99)
Δ RVOL	1.83***	2.07***	1.04*	1.24**	2.75***	0.91	1.26	0.02	0.22	1.22	3.76***	4.30***	3.26***	3.52***	3.98***
	(2.75)	(3.31)	(1.84)	(2.02)	(3.28)	(1.10)	(1.60)	(0.03)	(0.25)	(0.81)	(3.40)	(4.08)	(3.02)	(3.24)	(3.71)
RETEQ	−0.80***	−0.80***	−0.72***	−0.81***	−0.94***	−0.63***	−0.57***	−0.48***	−0.59***	−0.77***	−0.87***	−0.93***	−0.89***	−0.90***	−0.92***
	(−7.94)	(−8.71)	(−10.35)	(−9.28)	(−9.52)	(−4.38)	(−4.81)	(−4.93)	(−5.04)	(−3.60)	(−8.96)	(−9.19)	(−9.83)	(−8.83)	(−9.11)
Δ VIX	0.81***	0.95***	0.79***	0.87***	0.95***	1.98***	2.20***	1.85***	2.05***	4.00***	0.88***	0.88***	0.76***	0.89***	0.74***
	(6.53)	(7.88)	(7.26)	(7.50)	(6.85)	(5.65)	(7.91)	(7.54)	(8.03)	(6.79)	(7.16)	(7.42)	(7.19)	(7.51)	(5.98)
Δ SLOPE	−16.89***	−16.95***	−15.18***	−18.19***	−26.60***	−2.21	−2.99**	−1.43	−2.47*	5.03*	−23.25***	−22.82***	−21.75***	−23.70***	−25.28***
	(−10.98)	(−11.25)	(−10.60)	(−12.29)	(−13.28)	(−1.37)	(−2.30)	(−1.16)	(−1.69)	(1.95)	(−12.07)	(−12.83)	(−12.49)	(−12.59)	(−13.98)
Δ DEF	25.38***	30.58***	31.24***	29.84***	26.43***	128.86***	131.18***	113.82***	126.67***	192.94***	15.27***	20.56***	22.95***	21.42***	22.39***
	(8.23)	(9.91)	(10.10)	(9.52)	(8.65)	(9.84)	(10.54)	(10.65)	(10.90)	(9.06)	(4.98)	(6.45)	(7.94)	(7.19)	(6.98)
Cons	2.42***	1.85***	1.52***	2.29***	4.23***	1.98***	1.23***	0.77***	1.43***	2.14***	4.82***	4.35***	4.02***	4.56***	4.26***
	(26.01)	(24.50)	(25.31)	(27.90)	(19.04)	(13.28)	(10.21)	(6.79)	(12.13)	(5.02)	(16.32)	(16.48)	(15.76)	(15.33)	(16.88)
N	6494	7984	7548	7349	4703	3384	4623	4399	4045	1357	3110	3361	3149	3304	3346
adj. R^2	0.214	0.147	0.194	0.185	0.169	0.275	0.209	0.277	0.278	0.295	0.211	0.150	0.192	0.170	0.154

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Summary of model ML estimates

	mean	sd	min	5%	med	95%	max	N
κ^Q	0.16	0.17	-0.35	-0.15	0.17	0.47	0.50	253
$\kappa^Q\theta^Q$	-0.83	0.75	-2.57	-2.00	-0.88	0.57	1.34	253
σ^Q	1.45	0.40	0.52	0.97	1.33	2.23	2.74	253
κ^P	0.86	0.47	0.13	0.22	0.77	1.74	2.49	253
$\kappa^P\theta^P$	-4.58	2.42	-9.00	-8.72	-4.12	-1.02	-0.56	253
$\sigma(1)$	89.22	141.18	3.42	4.72	27.33	499.98	500.00	253
$\sigma(3)$	51.81	102.25	2.00	3.48	14.50	270.84	500.00	253
$\sigma(7)$	35.51	75.53	2.17	3.10	10.33	155.69	492.33	253
$\sigma(10)$	60.67	115.33	4.30	6.05	17.29	404.67	500.00	253
LLK	1891.52	628.79	163.67	627.53	2034.05	2686.96	2831.49	253
P	81.49	13.12	37.00	48.00	88.00	88.00	88.00	253

This table provides a summary statistics for ML estimates of the LogOU model. κ^Q and κ^P denote the mean-reversion rates under the risk-neutral and objective probability measures, respectively. θ^Q (θ^P) is the long-run mean of default intensity processes λ^Q under Q (P) measure. σ^Q is the instantaneous volatility of λ^Q process. Finally, $\sigma_\varepsilon(M)$ represents the volatility of the CDS misspricing, with M = 1, 3, 7, and 10-year maturities. *LLK* denotes the maximized value of the ML objective function.

Table 9: Summary Statistics of Distress Risk Premium by Rating and Sector

	Absolute DRP (bp)			Relative DRP (%)		
	mean	sd	med	mean	sd	med
Panel B.- By rating						
AA	22.24	32.86	7.45	27.52	24.66	30.27
A	31.18	50.68	19.45	44.73	31.24	54.49
BBB	49.89	109.52	31.11	43.76	29.23	51.30
BB	135.63	192.95	87.57	44.41	30.45	52.81
B	254.09	413.26	189.11	41.87	37.51	48.38
CCC	290.31	839.95	106.19	-2.67	115.58	22.51
Total	111.26	283.82	43.14	41.50	39.73	50.16
Panel B.- By sector						
Basic Materials	117.73	203.64	49.94	51.56	31.44	58.53
Consumer Goods	111.27	277.02	46.21	35.10	28.56	40.14
Consumer Services	136.91	376.26	53.33	49.45	23.15	54.65
Financials	103.05	369.02	21.64	10.86	73.44	25.05
Health Care	94.07	146.33	30.98	48.15	26.63	54.71
Industrials	85.65	117.23	39.03	50.53	26.30	57.57
Oil & Gas	95.71	123.44	47.42	48.09	22.97	53.24
Technology	141.82	325.89	56.45	48.91	24.07	52.68
Telecommunications	81.96	120.90	37.01	49.45	29.57	60.55
Utilities	104.65	134.61	53.84	46.67	29.95	56.83
Total	111.61	283.71	43.26	41.53	39.71	50.20

This table reports the summary statistics for the pooled time series of 5-year Distress Risk Premium (DRP) by rating (Panel A) and sector (Panel B). Absolute and relative DRPs are defined as $(CDS^Q - CDS^P)$ and $(CDS^Q - CDS^P)/CDS^Q$, respectively. The frequency of DRP is monthly. The sample spans from January 2004 until April 2011.

Table 10: Panel Data Analysis for Distress Risk Premium (*DRP*)

This table reports the results for the panel data regression,

$$\Delta DRP_{i,t} \quad = \quad \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} + \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t}$$

where $DRP_{i,t}$ is the 5-year CDS risk premium of name i for month t. DRP is defined as the difference of CDS^Q minus CDS^P. Liquidity proxies are the bid-ask spread ($ILBAS5y$), the number of contributors ($NOC5y$), the gamma measure of 5-year CDS contract ($ILCOV5y$), the return-to-volume measure ($ILRTV5y$) and the Fitch's liquidity ($LSCORE$) score. Finally, variable $Control_{i,t}$ is the vector of control variables which includes firm specific and global variables. Firm specific variables are the expected default frequency ($EDF1y$), the realized volatility of the stock returns ($RVOL$), the return on equity ($EQRET$) and the log of market capitalization (ME) of the underlying CDS names, respectively. The global variables considered are the VIX index (VIX), the slope of the interest rate curve ($SLOPE$) measured as the difference between 10-year Treasury bond and 3-month treasury bill yields and the difference between Moody's Aaa and Baa bond yield indexes (DEF). The model is estimated with issuer fixed effect. Robust standard errors are adjusted for issuer-clustering.

	01/2004 to 04/2011					01/2004 to 06/2007					06/2007 to 04/2011				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Δ ILBAS5y	1.24***					1.05***					1.47***				
	(10.55)					(7.24)					(6.92)				
Δ NOC5y		0.25***					0.11*					0.57***			
		(4.41)					(1.96)					(4.54)			
Δ ILCOV5y			1.65***					2.76***					1.17***		
			(7.31)					(4.97)					(4.72)		
Δ ILRTV5y				2.68***					4.56***					1.18**	
				(5.71)					(6.13)					(2.07)	
Δ LSCORE					−5.46***					−3.72**					−6.24***
					(−5.37)					(−2.57)					(−6.65)
Δ EDF1y	6.85***	3.78*	5.53*	4.51*	0.21	14.21***	7.78*	10.50**	6.49	8.94	2.92	−0.59	1.07	1.83	−0.11
	(2.62)	(1.84)	(1.79)	(1.91)	(0.10)	(2.69)	(1.91)	(2.53)	(1.53)	(0.98)	(1.47)	(−0.30)	(0.29)	(0.62)	(−0.05)
Δ RVOL	0.65*	0.88**	0.11	0.29	0.70	0.76	1.15**	−0.01	0.20	0.02	1.19*	1.54**	0.92	1.28*	1.25*
	(1.69)	(2.42)	(0.31)	(0.72)	(1.31)	(1.41)	(2.52)	(−0.02)	(0.36)	(0.02)	(1.94)	(2.32)	(1.45)	(1.88)	(1.89)
RETEQ	−0.49***	−0.48***	−0.49***	−0.51***	−0.56***	−0.38***	−0.37***	−0.33***	−0.41***	−0.44***	−0.52***	−0.55***	−0.61***	−0.56***	−0.55***
	(−8.00)	(−9.06)	(−9.22)	(−9.16)	(−9.36)	(−4.46)	(−5.40)	(−5.24)	(−5.34)	(−3.83)	(−8.69)	(−8.82)	(−8.93)	(−8.49)	(−8.98)
Δ VIX	0.55***	0.56***	0.53***	0.54***	0.59***	1.26***	1.18***	1.03***	1.20***	2.06***	0.66***	0.65***	0.63***	0.67***	0.56***
	(6.39)	(6.99)	(7.42)	(7.37)	(6.52)	(5.11)	(6.95)	(7.34)	(7.21)	(6.92)	(8.15)	(8.14)	(8.39)	(8.40)	(6.77)
Δ SLOPE	−10.78***	−10.19***	−9.25***	−11.57***	−16.01***	−0.91	−1.25	−0.32	−0.55	2.84**	−15.68***	−16.13***	−15.58***	−16.48***	−18.10***
	(−10.65)	(−10.58)	(−11.48)	(−11.34)	(−11.77)	(−0.85)	(−1.35)	(−0.42)	(−0.51)	(2.10)	(−13.15)	(−14.10)	(−14.05)	(−13.94)	(−15.23)
Δ DEF	20.11***	23.54***	22.79***	23.05***	21.28***	83.03***	79.95***	69.36***	82.85***	97.70***	14.60***	17.66***	17.28***	17.61***	18.92***
	(10.73)	(12.20)	(11.86)	(11.20)	(11.60)	(9.41)	(10.21)	(10.22)	(10.45)	(8.62)	(7.98)	(8.92)	(9.35)	(9.11)	(9.82)
Cons	1.40***	1.05***	0.85***	1.30***	2.49***	1.06***	0.53***	0.32***	0.69***	0.85***	3.06***	3.11***	2.86***	3.06***	2.97***
	(26.83)	(28.32)	(26.68)	(25.40)	(19.91)	(10.25)	(6.61)	(4.59)	(7.97)	(3.80)	(17.05)	(18.55)	(17.99)	(16.98)	(18.69)
N	6416	8298	7904	7356	4914	3406	5022	4823	4136	1650	3010	3276	3081	3220	3264
adj. R^2	0.196	0.127	0.175	0.159	0.166	0.233	0.156	0.236	0.234	0.230	0.212	0.153	0.187	0.171	0.166

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Panel Data Analysis for Default Risk Component (CDS^P)

This table reports the results for the panel data regression,

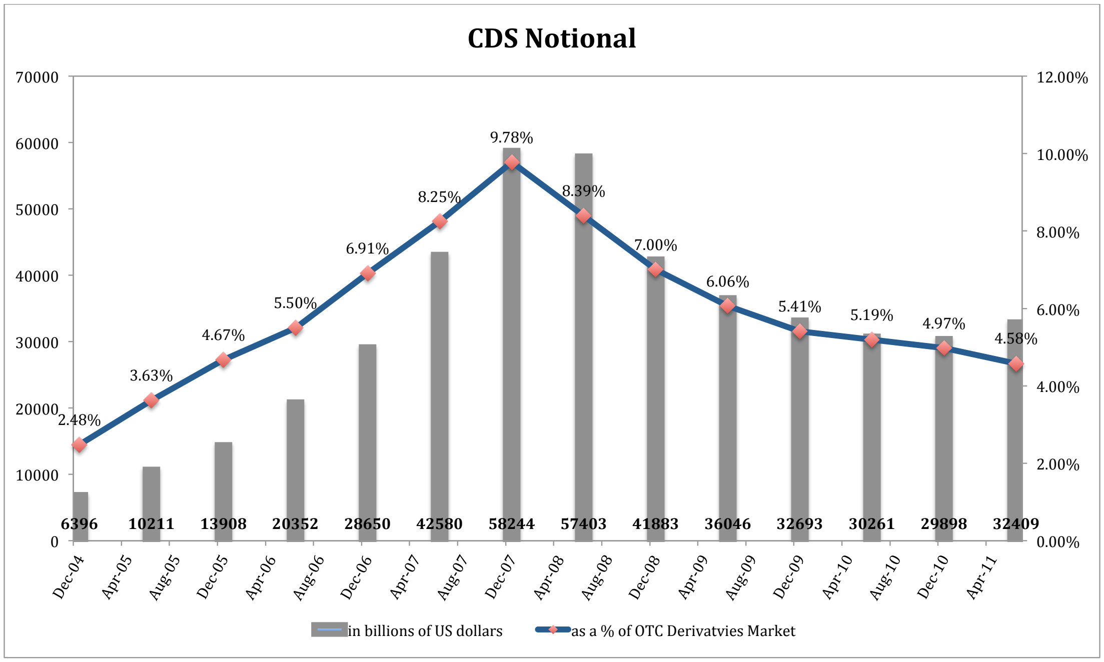
$$\Delta CDS^P_{i,t} \quad = \quad \alpha + \beta_1 \Delta ILBAS5y_{i,t} + \beta_2 \Delta NOC5y_{i,t} + \beta_3 \Delta ILCOV5y_{i,t} + \beta_4 \Delta ILRTV5y_{i,t} + \beta_5 \Delta LSCORE_{i,t} + \gamma \Delta Control_{i,t} + \varepsilon_{i,t}$$

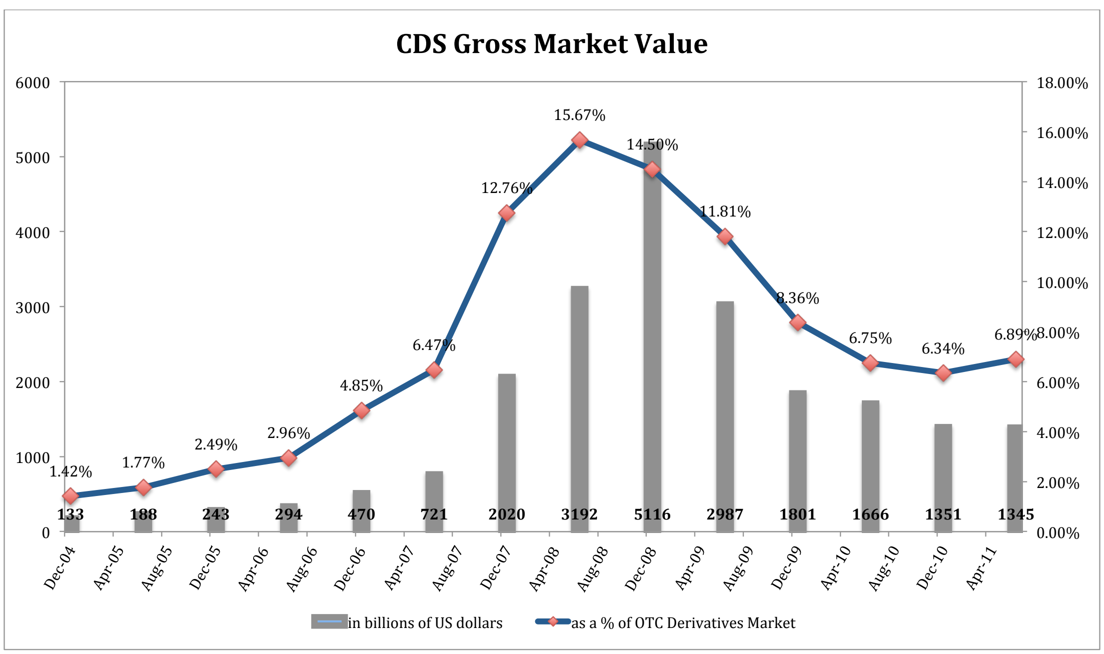
where $CDS^P_{i,t}$ is the 5-year CDS risk premium of name i for month t. DRP is defined as the difference of CDS^Q minus CDS^P. Liquidity proxies are the bid-ask spread ($ILBAS5y$), the number of contributors ($NOC5y$), the gamma measure of 5-year CDS contract ($ILCOV5y$), the return-to-volume measure ($ILRTV5y$) and the Fitch's liquidity ($LSCORE$) score. Finally, variable $Control_{i,t}$ is the vector of control variables which includes firm specific and global variables. Firm specific variables are the expected default frequency ($EDF1y$), the realized volatility of the stock returns ($RVOL$), the return on equity ($EQRET$) and the log of market capitalization (ME) of the underlying CDS names, respectively. The global variables considered are the VIX index (VIX), the slope of the interest rate curve ($SLOPE$) measured as the difference between 10-year Treasury bond and 3-month treasury bill yields and the difference between Moody's Aaa and Baa bond yield indexes (DEF). The model is estimated with issuer fixed effect. Robust standard errors are adjusted for issuer-clustering.

	01/2004 to 04/2011					01/2004 to 06/2007					06/2007 to 04/2011				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Δ ILBAS5y	0.84***					0.54***					1.32***				
	(6.50)					(5.58)					(5.12)				
Δ NOC5y		0.11*					0.06					0.21			
		(1.84)					(1.46)					(1.49)			
Δ ILCOV5y			0.95***					1.86***					0.52***		
			(4.68)					(4.79)					(3.28)		
Δ ILRTV5y				1.64***					2.50***					0.87**	
				(4.29)					(4.69)					(2.04)	
Δ LSCORE					−1.23					−0.74					−0.42
					(−1.58)					(−0.57)					(−0.39)
Δ EDF1y	5.77***	6.54***	6.15***	6.09***	3.81*	9.43***	11.09***	9.44***	8.32***	9.44	2.77	2.61	2.85	4.26**	2.65
	(2.95)	(3.50)	(4.20)	(4.04)	(1.96)	(4.02)	(5.57)	(4.50)	(4.37)	(1.14)	(1.09)	(1.17)	(1.42)	(2.15)	(1.18)
Δ RVOL	0.96***	0.91***	0.67**	0.59*	1.22***	0.50	0.63**	0.05	0.12	1.08**	1.75***	1.66***	1.70***	1.52***	1.61***
	(2.89)	(2.90)	(2.49)	(1.92)	(2.84)	(1.46)	(2.09)	(0.23)	(0.39)	(2.11)	(2.88)	(2.80)	(3.12)	(2.82)	(2.75)
RETEQ	−0.28***	−0.28***	−0.22***	−0.29***	−0.34***	−0.22***	−0.19***	−0.15***	−0.20***	−0.27***	−0.31***	−0.35***	−0.26***	−0.33***	−0.35***
	(−5.59)	(−6.02)	(−6.92)	(−6.22)	(−6.46)	(−3.51)	(−3.78)	(−3.67)	(−3.77)	(−2.92)	(−5.30)	(−5.84)	(−6.43)	(−5.70)	(−5.79)
Δ VIX	0.27***	0.30***	0.21***	0.26***	0.31***	0.72***	0.67***	0.53***	0.61***	1.13***	0.24***	0.25***	0.16***	0.25***	0.24***
	(4.63)	(5.65)	(4.99)	(5.25)	(4.64)	(4.19)	(5.32)	(6.13)	(5.17)	(4.81)	(3.99)	(4.22)	(3.57)	(4.41)	(3.58)
Δ SLOPE	−4.50***	−4.44***	−3.78***	−4.87***	−6.84***	−0.40	−0.50	−0.32	−0.27	1.86	−6.04***	−5.93***	−5.03***	−6.31***	−5.84***
	(−6.59)	(−6.68)	(−5.99)	(−7.17)	(−7.58)	(−0.66)	(−1.05)	(−0.65)	(−0.52)	(1.60)	(−6.88)	(−7.06)	(−6.37)	(−7.12)	(−6.40)
Δ DEF	5.32***	7.61***	7.39***	7.14***	5.89***	43.25***	41.57***	34.32***	39.81***	59.72***	0.82	3.64**	4.19***	3.78***	3.78**
	(3.54)	(5.12)	(6.08)	(5.06)	(3.89)	(6.46)	(6.99)	(7.66)	(6.90)	(5.97)	(0.48)	(2.28)	(3.46)	(2.67)	(2.30)
Cons	0.98***	0.75***	0.66***	0.93***	1.43***	0.86***	0.55***	0.34***	0.66***	0.80***	1.63***	1.40***	1.35***	1.53***	1.36***
	(16.93)	(18.69)	(24.17)	(18.94)	(13.48)	(14.84)	(12.33)	(7.45)	(15.35)	(4.42)	(10.25)	(10.11)	(11.12)	(10.61)	(10.72)
N	6332	7929	7515	7238	4740	3319	4671	4475	4042	1495	3013	3258	3040	3196	3245
adj. R^2	0.126	0.078	0.119	0.104	0.074	0.182	0.147	0.227	0.192	0.168	0.120	0.062	0.093	0.081	0.061

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

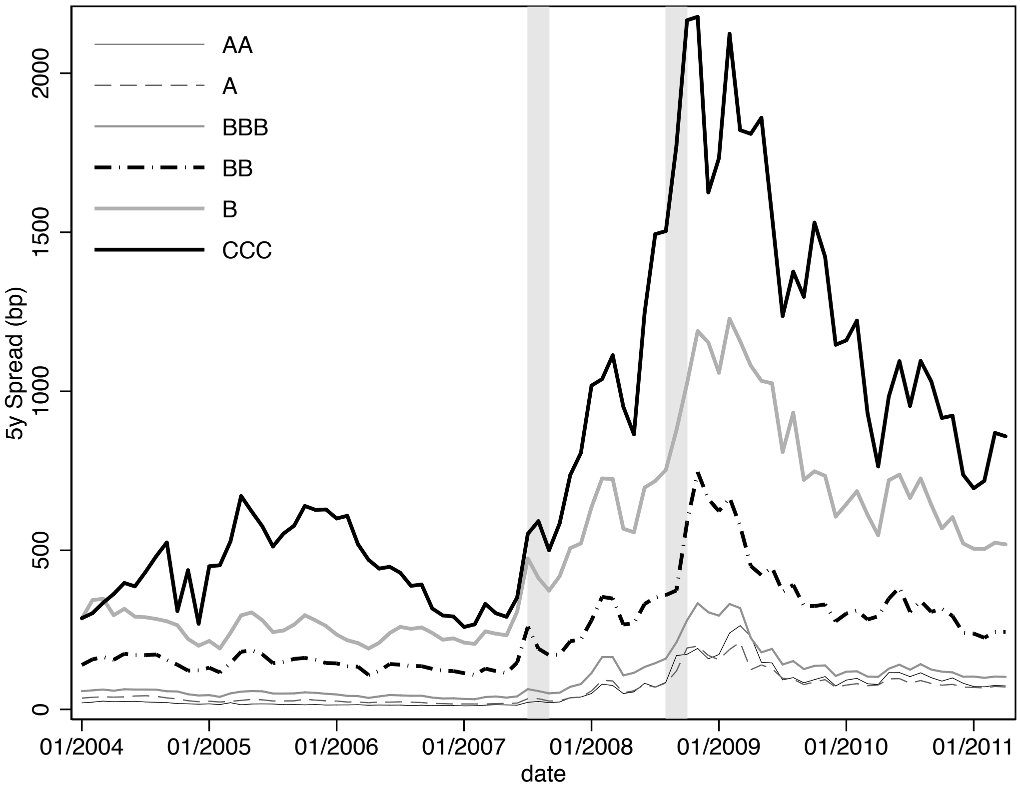
Figure 1: CDS Market Size





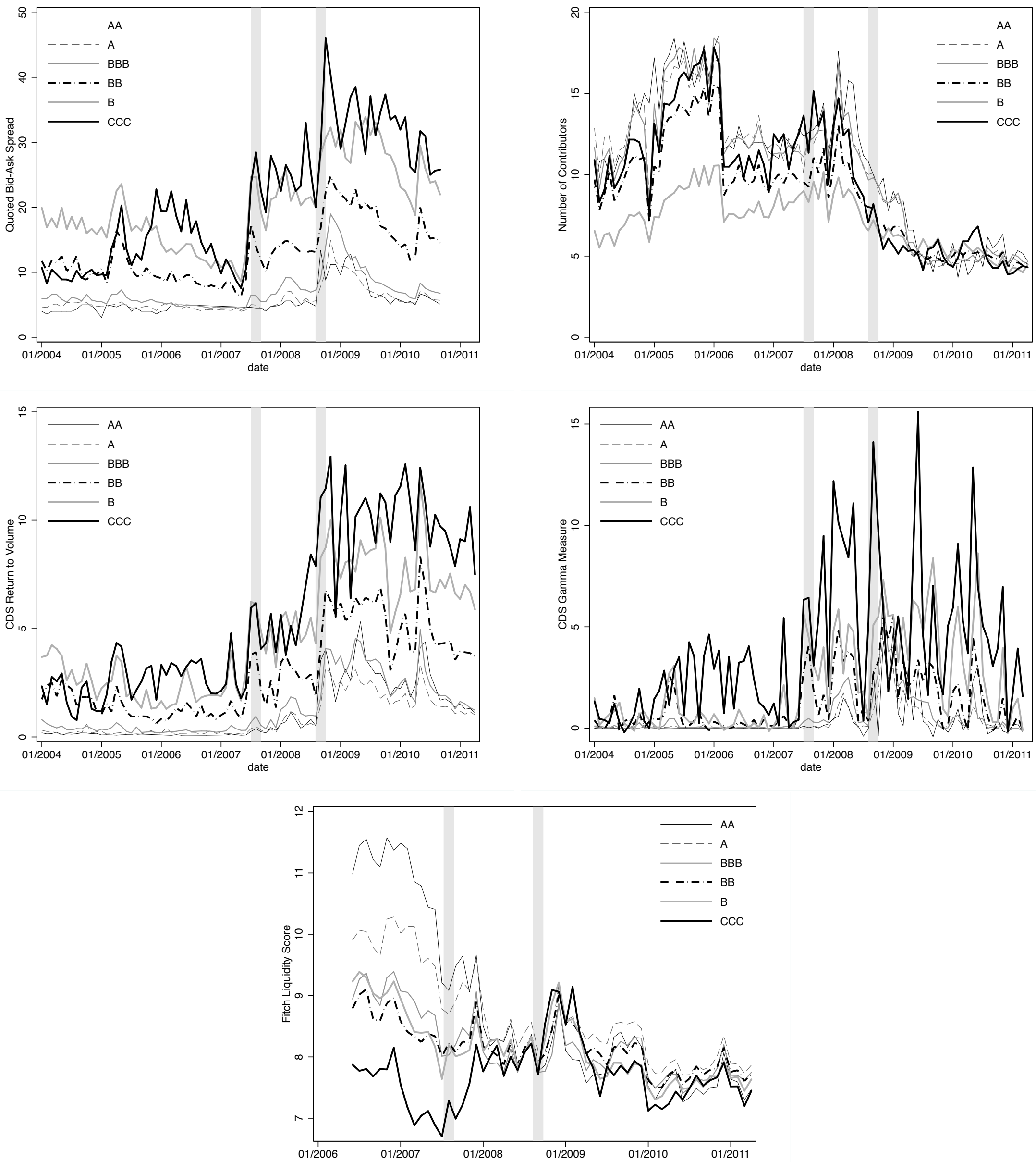
CDS market size in terms of notional amount (upper graph) and gross value (lower graph). Notional amount is the reference base for computing contractual CDS payments. Gross market value represents the mark-to-market value of open CDS contracts. Data is taken from semi-annual OTC derivatives market reports of BIS.

Figure 2: Time series of 5-year CDS spreads



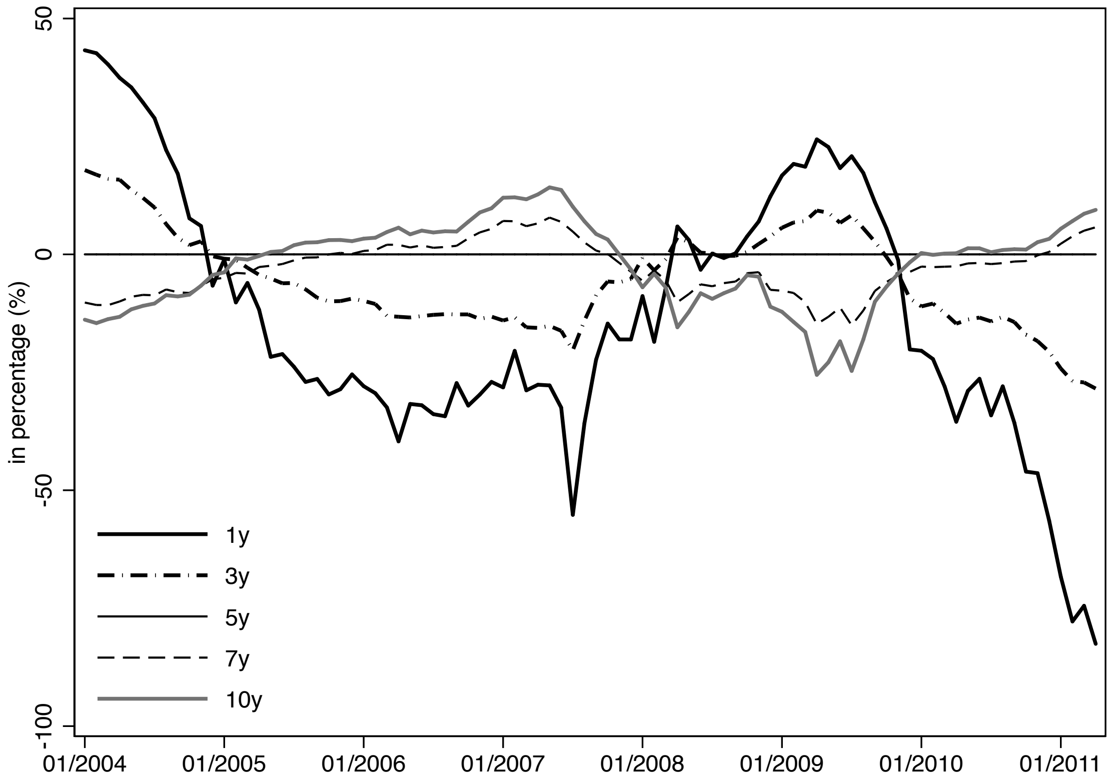
This figure graphs the averaged cross-sectional 5-year CDS spreads by rating group. The sample frequency is monthly and it spans from January 2004 to April, 2011. Vertical shadow lines indicate the suspension of three BNP Paribas funds in August, 2007, and the failure of Lehmann Brothers in September 2008, respectively.

Figure 3: Time series of Liquidity Measures



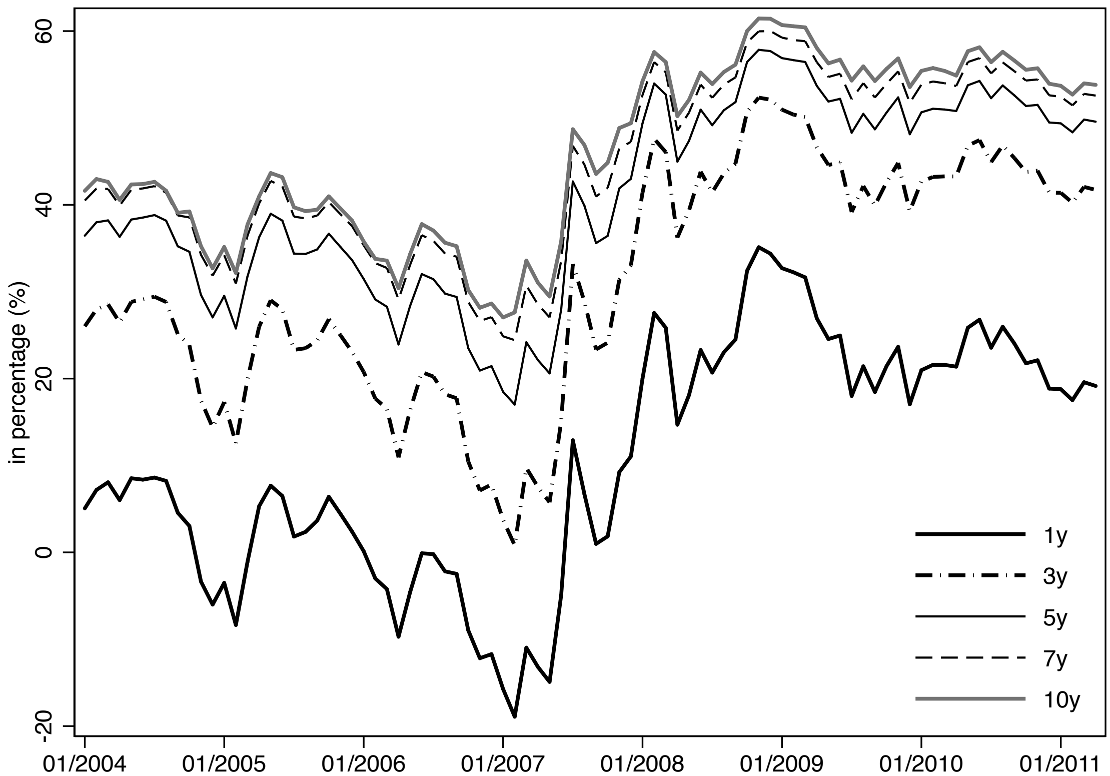
Time series of averaged cross-sectional liquidity measures by rating. Liquidity values outside the 5th and 95th percentiles have been removed.

Figure 4: Time series of Model Misspricing



This figure graphs the cross-sectional, averaged relative misspricing for the logOU model. Relative misspricing is defined as $MSP(M) = (CDS(M) - CDS^{Q}(M))/CDS^{Q}(M)$, where $CDS(M)$ is the market observed CDS spread with M year maturity, and $CDS^{Q}(M)$ is the model implied CDS spread under the risk neutral measure. The sample frequency is monthly and it spans from January 2004 to April, 2011.

Figure 5: Time series of Distress Risk Premium



Time series of relative distress risk premia (DRP) by maturity. Series are obtained by averaging the cross-sectional DRP within each month. The sample frequency is monthly and it spans from January 2004 to April, 2011.

A Log OU Model Estimates

Table 12: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
Alcoa Inc.	0.0625	-0.3803	1.2540	0.5254	-3.2313	0.0047	0.0022	0.0010	0.0018	2075.94
	(0.0151)	(0.0615)	(0.0161)	(0.3339)	(1.8216)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	
Barrick Gold Corp	0.0314	-0.3380	1.1767	0.3499	-2.0989	0.0012	0.0006	0.0006	0.0011	2462.27
	(0.0093)	(0.0348)	(0.0293)	(0.4905)	(2.7112)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Amern Elec Pwr Co Inc	0.3219	-1.8322	1.3759	1.1601	-7.0926	0.0010	0.0006	0.0003	0.0006	2587.04
	(0.0208)	(0.1089)	(0.0299)	(0.4774)	(3.1587)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
The AES Corp	0.0015	0.0129	1.4076	0.9730	-3.9564	0.0096	0.0050	0.0018	0.0036	1731.22
	(0.0060)	(0.0326)	(0.0755)	(1.1584)	(4.8464)	(0.0013)	(0.0007)	(0.0002)	(0.0001)	
Aetna Inc.	0.1009	-0.7840	1.3439	1.1892	-7.2334	0.0009	0.0004	0.0004	0.0007	2577.52
	(0.0143)	(0.0740)	(0.0373)	(0.6093)	(3.6079)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Amern Intl Gp Inc	0.0787	-0.4665	1.3109	0.2637	-1.5764	0.0461	0.0162	0.0099	0.0226	1223.83
	(0.0329)	(0.1217)	(0.0148)	(0.2237)	(1.1405)	(0.0060)	(0.0080)	(0.0013)	(0.0105)	
Intl Lease Fin Corp	0.0957	-0.6866	1.1769	0.1953	-0.8753	0.0243	0.0059	0.0042	0.0065	1567.99
	(0.0265)	(0.1132)	(0.0223)	(0.3125)	(1.3969)	(0.0029)	(0.0008)	(0.0023)	(0.0033)	
AK Stl Corp	0.2918	-1.3399	2.2028	0.8160	-3.0063	0.0112	0.0057	0.0025	0.0031	1646.54
	(0.0676)	(0.3243)	(0.0781)	(0.8166)	(4.0711)	(0.0021)	(0.0011)	(0.0002)	(0.0004)	
Allstate Corp	0.2111	-1.2641	1.2484	0.3865	-2.2828	0.0021	0.0009	0.0005	0.0009	2383.86
	(0.0122)	(0.0538)	(0.0185)	(0.3111)	(1.8170)	(0.0003)	(0.0001)	(0.0000)	(0.0001)	
Advanced Micro Devices Inc	0.5000	-1.3002	2.3401	0.5004	-3.1119	0.0209	0.0088	0.0129	0.0246	1088.75
	(0.0121)	(0.0619)	(0.0509)	(0.5045)	(2.6562)	(0.0019)	(0.0018)	(0.0029)	(0.0029)	
Amgen Inc.	0.1142	-0.8425	1.2902	0.6254	-3.9584	0.0007	0.0005	0.0004	0.0006	2634.00
	(0.0201)	(0.1041)	(0.0345)	(0.5455)	(3.5757)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	
Amkor Tech Inc	0.4987	-2.0002	2.7214	1.3307	-5.9422	0.0133	0.0046	0.0040	0.0059	1543.91
	(0.0959)	(0.4492)	(0.1047)	(1.2361)	(5.5080)	(0.0010)	(0.0005)	(0.0002)	(0.0004)	
AMR Corp	0.4916	-1.1141	2.1060	0.6272	-1.6053	0.0244	0.0122	0.0173	0.0303	1063.61
	(0.0075)	(0.0139)	(0.0374)	(0.3578)	(1.1924)	(0.0017)	(0.0010)	(0.0022)	(0.0042)	
Anadarko Pete Corp	0.0147	-0.2468	1.1175	0.6969	-3.8140	0.0044	0.0013	0.0006	0.0013	2197.15
	(0.0076)	(0.0324)	(0.0176)	(0.4091)	(2.0381)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	
ARAMARK Corp	0.0649	-0.1321	1.9090	2.0931	-8.7605	0.0074	0.0052	0.0015	0.0024	998.44
	(0.0370)	(0.1651)	(0.1272)	(1.9325)	(8.5347)	(0.0011)	(0.0012)	(0.0004)	(0.0006)	
ArvinMeritor Inc	0.4946	-1.6707	1.6235	0.4946	-2.1562	0.0500	0.0281	0.0110	0.0277	995.65
	(0.0101)	(0.0414)	(0.0266)	(0.3387)	(1.6281)	(0.0107)	(0.0361)	(0.0042)	(0.0334)	
Arrow Electrs Inc	0.1236	-0.7336	1.3638	1.4567	-8.1097	0.0019	0.0013	0.0009	0.0016	2224.87
	(0.0210)	(0.1048)	(0.0510)	(0.8928)	(5.2544)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	
AT&T Inc	0.2552	-1.3809	1.3109	0.6062	-3.7536	0.0010	0.0006	0.0006	0.0012	1810.04
	(0.0159)	(0.0774)	(0.0252)	(0.3779)	(2.3405)	(0.0001)	(0.0001)	(0.0002)	(0.0004)	
AT&T Mobility LLC	0.0394	-0.4951	1.3376	1.1265	-7.5196	0.0004	0.0004	0.0004	0.0007	1583.16
	(0.0379)	(0.2048)	(0.0514)	(1.1039)	(7.0539)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	
Avis Budget Group Inc	0.3741	-0.9837	1.0837	0.3741	-1.8763	0.0500	0.0499	0.0134	0.0384	409.31
	(0.0106)	(0.0366)	(0.0526)	(0.1865)	(0.8486)	(0.0034)	(0.0447)	(0.0053)	(0.0312)	
Avnet, Inc.	0.2339	-1.3042	1.6025	1.4415	-7.8239	0.0019	0.0013	0.0009	0.0017	2197.92
	(0.0237)	(0.1135)	(0.0399)	(0.5885)	(3.4181)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	
Amern Express Co	0.3170	-1.8557	1.4057	0.3929	-2.3845	0.0017	0.0009	0.0005	0.0010	2381.56
	(0.0134)	(0.0552)	(0.0172)	(0.2634)	(1.4592)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	
Autozone Inc	0.3061	-1.7715	1.6017	1.0518	-6.3495	0.0013	0.0010	0.0009	0.0015	2316.67
	(0.0332)	(0.1813)	(0.0542)	(0.7630)	(4.7857)	(0.0001)	(0.0002)	(0.0004)	(0.0005)	
Boeing Cap Corp	0.0920	-0.6946	1.2685	0.5743	-3.5326	0.0007	0.0005	0.0004	0.0006	2615.39
	(0.0093)	(0.0454)	(0.0288)	(0.4389)	(2.7609)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	
Bk of America Corp	0.0447	-0.4536	1.0659	0.1746	-0.9250	0.0043	0.0015	0.0007	0.0010	1599.95
	(0.0225)	(0.0919)	(0.0290)	(0.3657)	(1.7914)	(0.0005)	(0.0003)	(0.0001)	(0.0002)	
Baxter Intl Inc	0.2136	-1.2716	1.2101	1.1063	-7.3231	0.0004	0.0003	0.0003	0.0006	2809.56
	(0.0184)	(0.0996)	(0.0347)	(0.6959)	(4.8639)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	
Brunswick Corp	0.1329	-0.5517	1.1805	0.2598	-1.4403	0.0200	0.0049	0.0066	0.0074	1553.87
	(0.0389)	(0.1259)	(0.0190)	(0.2511)	(1.1591)	(0.0055)	(0.0005)	(0.0006)	(0.0016)	
Black& Decker Corp	0.2873	-1.6436	1.4608	0.3570	-2.3985	0.0010	0.0008	0.0008	0.0013	2400.31
	(0.0171)	(0.0870)	(0.0314)	(0.5166)	(2.9467)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Belo Corp.	0.3160	-1.3824	1.3155	2.0363	-6.2308	0.0296	0.0078	0.0041	0.0061	627.53
	(0.1677)	(0.6407)	(0.0844)	(1.4153)	(4.5091)	(0.0242)	(0.0040)	(0.0034)	(0.0064)	

Table 13: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
BellSouth Corp	0.2330	-1.2430	1.1334	1.2499	-8.3599	0.0004	0.0003	0.0005	0.0010	2657.07
	(0.0093)	(0.0510)	(0.0219)	(0.4472)	(3.0117)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	
Bristol Myers Squibb Co	0.2752	-1.5873	1.2337	1.1050	-7.4720	0.0004	0.0002	0.0002	0.0005	2831.49
	(0.0181)	(0.0965)	(0.0256)	(0.4651)	(3.2994)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Bombardier Inc	0.1640	-0.8328	1.7658	1.7079	-7.9361	0.0043	0.0020	0.0015	0.0024	1928.27
	(0.0225)	(0.1111)	(0.0520)	(0.8260)	(3.8816)	(0.0004)	(0.0002)	(0.0002)	(0.0004)	
Bombardier Cap Inc	-0.1299	0.4275	0.7089	0.3871	-1.7647	0.0034	0.0014	0.0007	0.0010	2219.77
	(0.0102)	(0.0373)	(0.0166)	(0.3621)	(1.5079)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	
Boston Pptys Ltd Partnership	-0.0015	-0.2538	1.2105	0.5891	-3.0027	0.0029	0.0013	0.0007	0.0014	1816.30
	(0.0029)	(0.0147)	(0.0347)	(0.6976)	(3.2352)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	
Berkshire Hathaway Inc	0.0676	-0.3604	0.7815	0.1902	-1.0734	0.0025	0.0012	0.0004	0.0007	2410.07
	(0.0067)	(0.0230)	(0.0118)	(0.1722)	(0.9112)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	
Boston Scientific Corp	0.0555	-0.4147	1.1502	0.4870	-2.7073	0.0027	0.0015	0.0009	0.0017	2171.80
	(0.0146)	(0.0612)	(0.0201)	(0.4928)	(2.6721)	(0.0006)	(0.0003)	(0.0002)	(0.0004)	
Boyd Gaming Corp	0.2762	-0.7019	1.8164	0.3484	-1.8484	0.0191	0.0151	0.0116	0.0168	1154.04
	(0.0478)	(0.2028)	(0.0379)	(0.4128)	(2.2650)	(0.0024)	(0.0014)	(0.0045)	(0.0066)	
ConAgra Foods Inc	-0.0552	0.0561	1.2583	0.4028	-2.3006	0.0009	0.0006	0.0007	0.0012	2449.39
	(0.0101)	(0.0366)	(0.0848)	(1.1754)	(7.2795)	(0.0002)	(0.0001)	(0.0003)	(0.0005)	
Cardinal Health Inc	0.0416	-0.4329	1.2955	1.3577	-8.2242	0.0009	0.0005	0.0006	0.0011	2481.17
	(0.0171)	(0.0907)	(0.0580)	(1.1935)	(7.1397)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
CA, Inc.	0.0212	-0.1725	1.3425	1.6319	-8.8535	0.0024	0.0018	0.0015	0.0030	1449.07
	(0.0143)	(0.0631)	(0.0567)	(1.1759)	(6.2492)	(0.0002)	(0.0003)	(0.0005)	(0.0009)	
Caterpillar Inc	0.1114	-0.7008	1.1190	0.6672	-4.1233	0.0007	0.0004	0.0004	0.0006	2614.72
	(0.0067)	(0.0328)	(0.0162)	(0.3709)	(2.1148)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Chubb Corp	0.0520	-0.5302	1.2047	0.8851	-5.2761	0.0007	0.0004	0.0003	0.0004	2686.96
	(0.0164)	(0.0873)	(0.0304)	(0.5980)	(3.4640)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	
CBS Corp	0.3232	-1.6915	1.6402	0.4193	-2.5690	0.0018	0.0009	0.0011	0.0017	1589.12
	(0.0185)	(0.0912)	(0.0354)	(0.4920)	(2.6909)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
Carnival Corp	0.0964	-0.7062	1.4155	0.7491	-4.3992	0.0011	0.0008	0.0012	0.0014	2335.58
	(0.0154)	(0.0692)	(0.0362)	(0.5359)	(3.1224)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Clear Channel Comms Inc	0.2131	-0.7516	1.1776	0.2131	-0.8922	0.0500	0.0500	0.0372	0.0491	367.49
	(0.0000)	(0.0000)	(0.0000)	(0.2543)	(1.1386)	(0.0023)	(0.0058)	(0.0046)	(0.0038)	
AVIS BUDGET CAR Rent LLC	0.2552	-0.4813	1.7326	0.3296	-1.8898	0.0500	0.0145	0.0492	0.0500	512.91
	(0.0127)	(0.0087)	(0.0441)	(0.3133)	(1.6908)	(0.0101)	(0.0034)	(0.0662)	(0.0346)	
Constellation Engy Gp Inc	0.1392	-0.8302	1.2898	0.5156	-2.8384	0.0043	0.0020	0.0006	0.0013	2159.98
	(0.0231)	(0.0935)	(0.0215)	(0.3349)	(1.9017)	(0.0006)	(0.0003)	(0.0001)	(0.0002)	
Chesapeake Engy Corp	0.0034	-0.0599	1.6489	1.4748	-7.5095	0.0066	0.0043	0.0017	0.0025	1831.40
	(0.0069)	(0.0401)	(0.0527)	(0.7393)	(3.7179)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	
Cigna Corp	0.1271	-0.8367	1.2981	1.3136	-7.4444	0.0008	0.0006	0.0004	0.0007	2545.88
	(0.0094)	(0.0477)	(0.0264)	(0.4605)	(2.6040)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
CIT Gp Inc	0.3841	-1.0825	2.5702	0.3841	-2.2011	0.0500	0.0167	0.0397	0.0500	589.75
	(0.0099)	(0.0378)	(0.0411)	(0.5508)	(2.3279)	(0.0095)	(0.0037)	(0.0168)	(0.0287)	
Celestica Inc	-0.2725	1.1172	0.9452	1.7369	-7.2214	0.0064	0.0036	0.0022	0.0031	1794.68
	(0.0297)	(0.1168)	(0.0351)	(0.9624)	(3.9432)	(0.0007)	(0.0004)	(0.0003)	(0.0004)	
Comcast Corp	0.1723	-1.0007	1.3743	0.8843	-5.2007	0.0011	0.0006	0.0005	0.0009	2450.71
	(0.0106)	(0.0526)	(0.0257)	(0.3907)	(2.4167)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Comcast Cable Comms LLC	0.1544	-0.9451	1.3307	1.3878	-8.8781	0.0009	0.0006	0.0006	0.0011	2476.49
	(0.0185)	(0.0954)	(0.0334)	(0.5772)	(3.7163)	(0.0001)	(0.0000)	(0.0001)	(0.0002)	
CMS Engy Corp	0.3601	-1.9275	1.8581	1.6097	-7.7539	0.0023	0.0015	0.0009	0.0013	2168.17
	(0.0358)	(0.1874)	(0.0564)	(0.7982)	(4.5492)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	
New Cingular Wireless Services Inc	0.1848	-1.0860	1.2437	1.1707	-8.1733	0.0003	0.0002	0.0004	0.0009	2454.33
	(0.0297)	(0.1549)	(0.0331)	(0.5765)	(4.1828)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	
Cdn Nat Res Ltd	0.0467	-0.2968	0.9442	0.3383	-1.8176	0.0015	0.0007	0.0007	0.0013	2373.55
	(0.0076)	(0.0260)	(0.0237)	(0.4729)	(2.3752)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Cap One Finl Corp	0.2775	-1.3874	1.0305	0.3860	-1.7242	0.0027	0.0013	0.0008	0.0013	2160.66
	(0.0103)	(0.0437)	(0.0114)	(0.1804)	(0.9598)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	
Cap One Bk USA Natl Assn	0.1614	-1.0120	1.0368	0.7645	-3.0793	0.0027	0.0014	0.0008	0.0013	911.17
	(0.0299)	(0.1226)	(0.0483)	(0.8438)	(3.2480)	(0.0009)	(0.0005)	(0.0002)	(0.0003)	
Cooper Tire& Rubr Co	0.2992	-1.3842	2.0815	0.6029	-3.3937	0.0086	0.0046	0.0047	0.0073	1584.20
	(0.0611)	(0.2405)	(0.0378)	(0.5310)	(2.7834)	(0.0005)	(0.0005)	(0.0004)	(0.0008)	

Table 14: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
ConocoPhillips	0.2232	-1.3463	1.2370	0.6564	-4.2100	0.0005	0.0004	0.0002	0.0005	2759.83
	(0.0117)	(0.0674)	(0.0298)	(0.4797)	(3.0519)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Cox Comms Inc	0.2588	-1.4550	1.4826	1.3347	-8.1593	0.0015	0.0009	0.0006	0.0011	2358.95
	(0.0160)	(0.0814)	(0.0283)	(0.4267)	(2.6582)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Campbell Soup Co	0.0046	-0.2751	1.2644	1.3648	-8.8973	0.0005	0.0004	0.0005	0.0009	2642.32
	(0.0045)	(0.0458)	(0.0677)	(1.1911)	(8.0304)	(0.0001)	(0.0000)	(0.0001)	(0.0002)	
Computer Sciences Corp	-0.1603	0.6837	1.2584	1.1149	-6.7208	0.0013	0.0013	0.0009	0.0016	2267.32
	(0.0242)	(0.1160)	(0.0633)	(1.1575)	(7.1089)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	
Cisco Sys Inc	0.1725	-1.0986	1.3183	0.5825	-3.9116	0.0005	0.0005	0.0005	0.0008	2288.17
	(0.0205)	(0.1011)	(0.0304)	(0.7055)	(4.5723)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	
CSX Corp	0.1320	-0.8404	1.2795	1.0350	-6.1825	0.0010	0.0005	0.0005	0.0010	2489.75
	(0.0124)	(0.0646)	(0.0341)	(0.5878)	(3.3953)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	
Centex Corp	0.4029	-2.2276	1.7107	0.4782	-2.5314	0.0039	0.0021	0.0012	0.0022	2017.59
	(0.0251)	(0.1166)	(0.0314)	(0.3834)	(2.1573)	(0.0009)	(0.0005)	(0.0003)	(0.0006)	
CVS Caremark Corp	0.2986	-1.8149	1.4980	0.9008	-5.3929	0.0010	0.0007	0.0007	0.0011	1311.57
	(0.0337)	(0.1717)	(0.0591)	(1.1344)	(6.7489)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	
Cmnty Health Sys Inc	0.4883	-2.0225	2.7305	1.9671	-8.9998	0.0061	0.0053	0.0023	0.0035	903.69
	(0.1942)	(0.8924)	(0.2192)	(2.7238)	(12.8093)	(0.0010)	(0.0014)	(0.0009)	(0.0009)	
Dominion Res Inc	0.3680	-2.0247	1.3698	1.3691	-8.7390	0.0007	0.0004	0.0003	0.0006	2646.82
	(0.0181)	(0.0918)	(0.0242)	(0.3843)	(2.5765)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	
E I du Pont de Nemours& Co	0.1539	-0.9834	1.2864	0.7627	-5.0651	0.0007	0.0005	0.0004	0.0007	2630.13
	(0.0109)	(0.0626)	(0.0365)	(0.7045)	(4.5069)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	
Dillards Inc	0.0915	-0.3033	2.0420	0.8639	-4.3677	0.0105	0.0045	0.0040	0.0062	1600.64
	(0.0486)	(0.2119)	(0.0772)	(0.8324)	(3.8618)	(0.0010)	(0.0005)	(0.0010)	(0.0015)	
Deere& Co	0.1021	-0.7816	1.3032	1.2362	-7.8069	0.0010	0.0003	0.0004	0.0007	2610.51
	(0.0086)	(0.0497)	(0.0328)	(0.6288)	(3.7371)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	
Dell Inc	0.0430	-0.3713	1.1194	0.4362	-2.6057	0.0012	0.0007	0.0005	0.0009	2496.26
	(0.0103)	(0.0482)	(0.0286)	(0.5663)	(3.2930)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Quest Diagnostics Inc	-0.1141	0.3454	1.1104	1.4150	-7.7591	0.0016	0.0011	0.0007	0.0013	2242.41
	(0.0230)	(0.1047)	(0.0543)	(1.1858)	(6.2989)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	
Walt Disney Co	0.2858	-1.5342	1.2423	0.6825	-4.5463	0.0005	0.0003	0.0004	0.0008	2668.48
	(0.0126)	(0.0648)	(0.0214)	(0.3712)	(2.5700)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	
Dean Hldg Co	-0.2711	1.0882	0.9679	0.6047	-2.4204	0.0064	0.0039	0.0020	0.0035	1622.54
	(0.0346)	(0.1434)	(0.0414)	(0.9799)	(4.0269)	(0.0012)	(0.0010)	(0.0002)	(0.0002)	
Dean Foods Co	-0.3453	1.3357	0.8722	2.4475	-8.8622	0.0076	0.0046	0.0021	0.0030	975.99
	(0.0632)	(0.2418)	(0.0577)	(1.9170)	(7.2270)	(0.0015)	(0.0016)	(0.0013)	(0.0013)	
R R Donnelley& Sons Co	0.2333	-1.2715	1.7480	0.4636	-2.7793	0.0030	0.0019	0.0012	0.0019	1818.83
	(0.0258)	(0.1206)	(0.0365)	(0.4943)	(3.0065)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	
Domtar Corp	0.2371	-1.3318	2.0517	1.6852	-7.4213	0.0055	0.0028	0.0014	0.0016	857.52
	(0.0763)	(0.3897)	(0.1828)	(1.8329)	(7.8789)	(0.0009)	(0.0005)	(0.0005)	(0.0004)	
Dow Chem Co	0.1827	-1.0140	1.2893	0.4478	-2.6745	0.0021	0.0014	0.0007	0.0014	2261.83
	(0.0101)	(0.0411)	(0.0221)	(0.3270)	(1.9555)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	
Darden Restaurants Inc	0.1460	-0.8358	1.2378	0.4728	-2.6889	0.0020	0.0011	0.0011	0.0018	2227.49
	(0.0162)	(0.0703)	(0.0328)	(0.5949)	(3.3705)	(0.0004)	(0.0002)	(0.0005)	(0.0006)	
DIRECTV Hldgs LLC	-0.0153	0.0294	1.5190	1.6792	-9.0000	0.0024	0.0017	0.0018	0.0029	1903.34
	(0.0100)	(0.0463)	(0.0567)	(0.9138)	(4.7118)	(0.0003)	(0.0002)	(0.0004)	(0.0005)	
Duke Energy Carolinas LLC	0.0943	-0.6960	1.1892	1.0617	-6.5459	0.0007	0.0005	0.0003	0.0005	1646.36
	(0.0211)	(0.1043)	(0.0366)	(0.6863)	(4.2776)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Devon Engy Corp	0.2944	-1.6488	1.3034	1.1031	-6.9446	0.0007	0.0004	0.0003	0.0006	2654.52
	(0.0148)	(0.0800)	(0.0271)	(0.4412)	(2.8356)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
Dynegy Hldgs Inc	-0.0694	0.3342	1.6499	1.1403	-3.9568	0.0254	0.0122	0.0030	0.0049	1445.60
	(0.0537)	(0.2369)	(0.0707)	(0.9621)	(3.5544)	(0.0040)	(0.0019)	(0.0003)	(0.0004)	
Energy Future Hldgs Corp	-0.1464	0.6090	1.2232	0.7369	-1.5602	0.0500	0.0238	0.0083	0.0148	514.79
	(0.1117)	(0.2964)	(0.0479)	(1.0598)	(2.1446)	(0.0121)	(0.0083)	(0.0025)	(0.0046)	
Eastman Kodak Co	-0.1973	1.1075	1.6536	0.7425	-3.3240	0.0173	0.0072	0.0048	0.0086	1462.22
	(0.0541)	(0.2096)	(0.0392)	(0.6264)	(2.8347)	(0.0015)	(0.0007)	(0.0011)	(0.0021)	
Embarq Corp	-0.0493	0.1333	1.3101	1.4992	-8.1891	0.0018	0.0017	0.0013	0.0026	1393.73
	(0.0193)	(0.0839)	(0.0576)	(1.0311)	(5.3603)	(0.0003)	(0.0002)	(0.0005)	(0.0008)	
Eastman Chem Co	0.2747	-1.5216	1.4180	1.1403	-6.8149	0.0010	0.0008	0.0007	0.0012	2402.50
	(0.0212)	(0.1165)	(0.0462)	(0.7225)	(4.4331)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	

Table 15: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
EOP Oper Ltd Pship	0.1446	-0.9755	1.4544	1.2546	-7.3412	0.0016	0.0012	0.0008	0.0017	2278.75
	(0.0369)	(0.1898)	(0.0691)	(1.0960)	(6.6246)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	
El Paso Corp	0.2578	-1.2758	1.9207	1.3542	-6.2045	0.0059	0.0039	0.0013	0.0019	1877.58
	(0.0397)	(0.1833)	(0.0518)	(0.7301)	(3.6416)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	
ERP Oper Ltd Pship	0.0627	-0.6846	1.4886	0.5222	-2.9534	0.0031	0.0010	0.0007	0.0013	2240.74
	(0.0210)	(0.0788)	(0.0429)	(0.7041)	(3.6174)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	
EXPEDIA INC	0.2568	-1.3446	1.6970	1.4087	-7.1536	0.0042	0.0024	0.0020	0.0033	1203.69
	(0.0300)	(0.1438)	(0.0688)	(0.9911)	(5.0214)	(0.0006)	(0.0004)	(0.0010)	(0.0016)	
Ford Mtr Co	0.3460	-1.1781	1.4164	0.3622	-1.4289	0.0500	0.0500	0.0281	0.0493	442.07
	(0.0000)	(0.0000)	(0.0000)	(0.4303)	(1.0951)	(0.0159)	(0.0460)	(0.0082)	(0.0113)	
Hertz Corp	0.3113	-1.3447	2.1638	0.9745	-5.2494	0.0106	0.0057	0.0045	0.0076	1553.13
	(0.0980)	(0.4045)	(0.0476)	(0.6918)	(3.3264)	(0.0012)	(0.0009)	(0.0017)	(0.0026)	
FORD Mtr Cr Co LLC	0.5000	-2.0171	2.5224	0.7688	-4.2365	0.0490	0.0176	0.0098	0.0221	586.08
	(0.1557)	(0.7755)	(0.0949)	(0.9261)	(4.5618)	(0.0197)	(0.0156)	(0.0044)	(0.0228)	
Freeport McMoran Copper& Gold Inc	-0.0334	0.0608	1.2343	1.2386	-5.7344	0.0043	0.0025	0.0030	0.0034	1616.55
	(0.0128)	(0.0498)	(0.0402)	(0.7059)	(3.1994)	(0.0004)	(0.0002)	(0.0002)	(0.0004)	
1st Data Corp	-0.1287	0.5416	1.3173	0.1997	-1.0144	0.0249	0.0088	0.0041	0.0067	1459.92
	(0.0454)	(0.1814)	(0.0273)	(0.3468)	(1.7083)	(0.0029)	(0.0013)	(0.0008)	(0.0012)	
FirstEnergy Corp	-0.0417	0.0537	1.0551	0.6984	-3.5325	0.0022	0.0012	0.0006	0.0011	2298.70
	(0.0082)	(0.0314)	(0.0351)	(0.7071)	(3.7482)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	
Fairfax Finl Hldgs Ltd	-0.3108	1.1136	0.6902	0.7261	-2.6160	0.0055	0.0034	0.0020	0.0025	1807.47
	(0.0260)	(0.0975)	(0.0212)	(0.6087)	(2.1249)	(0.0005)	(0.0002)	(0.0002)	(0.0004)	
Fortune Brands Inc	0.2019	-1.1953	1.4979	0.5928	-3.7140	0.0021	0.0012	0.0010	0.0016	2216.02
	(0.0215)	(0.0996)	(0.0262)	(0.3826)	(2.3024)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	
Freescale Semiconductor Inc	0.1275	-0.2774	1.6695	0.1341	-0.6818	0.0490	0.0241	0.0470	0.0500	674.78
	(0.0220)	(0.0344)	(0.0307)	(0.2610)	(1.2757)	(0.0169)	(0.0128)	(0.0404)	(0.0181)	
Fst Oil Corp	0.0063	-0.0740	1.7350	1.2321	-5.9704	0.0058	0.0042	0.0017	0.0027	1834.46
	(0.0107)	(0.0519)	(0.0775)	(1.0190)	(4.8815)	(0.0006)	(0.0006)	(0.0002)	(0.0004)	
Gannett Co Inc DE	0.1923	-0.9319	1.2247	0.2192	-1.2211	0.0123	0.0049	0.0025	0.0038	1761.98
	(0.0350)	(0.1260)	(0.0270)	(0.2756)	(1.5774)	(0.0011)	(0.0006)	(0.0010)	(0.0016)	
Gen Elec Cap Corp	0.1525	-0.9589	1.2289	0.3142	-1.7823	0.0033	0.0010	0.0007	0.0011	2261.45
	(0.0102)	(0.0413)	(0.0179)	(0.3143)	(1.6091)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	
Gen Mls Inc	0.2953	-1.6712	1.3036	0.7996	-5.1224	0.0006	0.0004	0.0004	0.0007	2648.04
	(0.0188)	(0.1042)	(0.0336)	(0.5282)	(3.5309)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
Residential Cap LLC	0.2530	-0.9905	1.3902	0.2867	-0.7308	0.0500	0.0500	0.0500	0.0500	-1167.05
	(0.0024)	(0.0000)	(0.0000)	(0.2972)	(1.1372)	(0.0005)	(0.0017)	(0.0178)	(0.0045)	
GMAC LLC	0.4070	-1.2883	2.6925	0.4733	-2.4466	0.0500	0.0309	0.0116	0.0286	367.44
	(0.0802)	(0.1443)	(0.0841)	(0.7912)	(3.5892)	(0.0136)	(0.0253)	(0.0110)	(0.0576)	
G A T X Corp	0.1230	-0.7557	1.3086	0.7556	-3.8137	0.0020	0.0013	0.0008	0.0014	2240.52
	(0.0163)	(0.0725)	(0.0326)	(0.5282)	(2.8844)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	
GA PACIFIC LLC	0.1273	-0.6389	1.8959	1.4149	-7.1941	0.0057	0.0027	0.0019	0.0031	1074.29
	(0.0358)	(0.1564)	(0.0870)	(1.3602)	(6.5438)	(0.0009)	(0.0005)	(0.0004)	(0.0009)	
The Gap Inc	-0.1467	0.6072	1.1275	0.9265	-5.0133	0.0016	0.0011	0.0013	0.0021	2197.22
	(0.0359)	(0.1666)	(0.0734)	(1.3808)	(7.7597)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	
Goodrich Corp	0.2703	-1.5237	1.3262	1.1083	-6.7728	0.0008	0.0005	0.0004	0.0007	2579.67
	(0.0202)	(0.1083)	(0.0326)	(0.5801)	(3.8280)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Goodyear Tire& Rubr Co	0.1985	-0.8562	2.0866	1.8121	-7.5002	0.0103	0.0062	0.0029	0.0047	1602.94
	(0.0659)	(0.2963)	(0.0684)	(0.7769)	(3.5418)	(0.0015)	(0.0010)	(0.0011)	(0.0015)	
Halliburton Co	0.1315	-0.8136	1.1373	1.0102	-5.8450	0.0007	0.0005	0.0003	0.0007	2613.37
	(0.0081)	(0.0483)	(0.0293)	(0.5481)	(3.1487)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
HCA Inc.	-0.0295	0.4052	1.8913	1.0638	-6.0129	0.0058	0.0044	0.0031	0.0049	1706.07
	(0.0261)	(0.1040)	(0.0486)	(0.8598)	(4.4519)	(0.0006)	(0.0007)	(0.0015)	(0.0023)	
Home Depot Inc	0.1695	-0.9744	1.1619	0.2619	-1.6744	0.0011	0.0007	0.0006	0.0010	2474.87
	(0.0070)	(0.0322)	(0.0202)	(0.3041)	(1.8646)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Hess Corp	0.0951	-0.5390	1.0355	0.4459	-2.3946	0.0012	0.0008	0.0007	0.0015	1584.58
	(0.0122)	(0.0467)	(0.0342)	(0.6307)	(3.1938)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	
Harrahs Oper Co Inc	0.1985	-0.5309	0.8366	0.1985	-0.7842	0.0500	0.0500	0.0202	0.0500	437.84
	(0.0000)	(0.0000)	(0.0000)	(0.1374)	(0.6465)	(0.0046)	(0.0068)	(0.0030)	(0.0067)	
Hartford Finl Svcs Gp Inc	0.1824	-1.1101	1.4502	0.2621	-1.5179	0.0067	0.0019	0.0009	0.0015	2058.31
	(0.0215)	(0.1037)	(0.0224)	(0.3218)	(1.7471)	(0.0011)	(0.0004)	(0.0001)	(0.0003)	

Table 16: Parameters

Country	κ^{Q}	$\kappa^{Q}\theta^{Q}$	σ^{Q}	κ^{P}	$\kappa^{P}\theta^{P}$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
Honeywell Intl Inc	0.1983	-1.1526	1.1474	0.6205	-4.0413	0.0004	0.0002	0.0003	0.0005	2800.51
	(0.0089)	(0.0544)	(0.0291)	(0.4938)	(3.1649)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Host Hotels& Resorts Inc	0.4238	-2.0809	2.2317	0.7019	-4.0665	0.0052	0.0027	0.0020	0.0028	1264.08
	(0.0452)	(0.2071)	(0.0528)	(0.7638)	(3.7685)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	
Host Hotels& Resorts LP	0.2662	-1.2699	1.9740	1.2003	-6.4937	0.0068	0.0020	0.0024	0.0035	1246.74
	(0.0430)	(0.1883)	(0.0415)	(0.8296)	(3.8262)	(0.0010)	(0.0004)	(0.0010)	(0.0010)	
Starwood Hotels& Resorts Wwide Inc	0.4296	-2.2311	1.8111	1.6121	-8.3511	0.0029	0.0017	0.0014	0.0023	2034.05
	(0.0245)	(0.1198)	(0.0434)	(0.5506)	(3.0387)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	
K Hovnanian Entpers Inc	0.4692	-1.1960	2.0713	0.4693	-2.3695	0.0208	0.0095	0.0111	0.0218	1000.05
	(0.0219)	(0.0725)	(0.0634)	(0.4130)	(1.6541)	(0.0013)	(0.0010)	(0.0041)	(0.0085)	
Hewlett Packard Co	0.2134	-1.2684	1.2784	0.9783	-6.5686	0.0005	0.0003	0.0004	0.0007	2697.80
	(0.0170)	(0.0879)	(0.0262)	(0.4652)	(3.1173)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	
Intl Business Machs Corp	0.2430	-1.4018	1.2428	0.5705	-3.9305	0.0004	0.0002	0.0003	0.0006	2775.43
	(0.0112)	(0.0597)	(0.0199)	(0.3461)	(2.2679)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Intl Paper Co	0.2252	-1.2398	1.5149	0.9198	-5.3366	0.0024	0.0012	0.0009	0.0015	2200.51
	(0.0108)	(0.0479)	(0.0284)	(0.4242)	(2.4588)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	
Ingersoll Rand Co	0.2734	-1.5222	1.2212	0.8951	-5.7265	0.0007	0.0005	0.0005	0.0009	2587.34
	(0.0193)	(0.0998)	(0.0276)	(0.4788)	(2.9875)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Iron Mtn Inc	-0.0297	0.1895	1.5893	1.8343	-8.2291	0.0034	0.0031	0.0018	0.0021	1567.58
	(0.0304)	(0.1385)	(0.0963)	(1.4047)	(6.6028)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	
Johnson Ctls Inc	0.1216	-0.8346	1.4128	0.3615	-2.1790	0.0013	0.0009	0.0005	0.0009	2404.20
	(0.0098)	(0.0480)	(0.0211)	(0.4144)	(2.1791)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
J C Penney Co Inc	0.2103	-1.2103	1.6244	1.1403	-6.0197	0.0035	0.0018	0.0013	0.0021	2010.69
	(0.0221)	(0.1160)	(0.0349)	(0.4744)	(2.5843)	(0.0008)	(0.0005)	(0.0003)	(0.0004)	
Nordstrom Inc	0.2261	-1.2674	1.4000	0.4039	-2.5312	0.0015	0.0009	0.0009	0.0015	2304.83
	(0.0111)	(0.0415)	(0.0276)	(0.3366)	(2.3058)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	
KB Home	0.4105	-2.2546	2.1794	1.2219	-5.7390	0.0096	0.0042	0.0025	0.0040	1712.64
	(0.0653)	(0.3051)	(0.0729)	(0.7689)	(3.9483)	(0.0016)	(0.0010)	(0.0005)	(0.0009)	
Kraft Foods Inc	0.2201	-1.2747	1.3149	0.8576	-5.5090	0.0006	0.0005	0.0005	0.0009	2565.75
	(0.0161)	(0.0860)	(0.0345)	(0.5619)	(3.6017)	(0.0001)	(0.0000)	(0.0001)	(0.0002)	
Kerr Mcgee Corp	0.0259	-0.2908	1.1143	1.0679	-6.0046	0.0027	0.0012	0.0006	0.0011	2283.52
	(0.0117)	(0.0509)	(0.0304)	(0.5911)	(3.2915)	(0.0005)	(0.0002)	(0.0000)	(0.0001)	
Kinder Morgan Engy Partners L P	0.0464	-0.3380	1.0767	0.6741	-3.6888	0.0016	0.0008	0.0005	0.0009	2401.78
	(0.0126)	(0.0510)	(0.0246)	(0.5649)	(3.0159)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	
The Kroger Co.	0.3601	-1.8829	1.3782	0.8913	-5.3515	0.0013	0.0008	0.0008	0.0014	2371.39
	(0.0307)	(0.1578)	(0.0473)	(0.7190)	(4.5373)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	
Kohls Corp	0.1154	-0.8258	1.4212	0.8215	-5.0241	0.0013	0.0007	0.0008	0.0011	2394.60
	(0.0133)	(0.0627)	(0.0394)	(0.5936)	(3.6162)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	
Lear Corp	-0.2472	0.2960	0.1909	0.0648	-0.0212	0.0500	0.0499	0.0498	0.0491	-5775.63
	(0.0000)	(0.0000)	(0.0000)	(0.0329)	(0.0541)	(0.0005)	(0.0013)	(0.0060)	(0.0007)	
Lennar Corp	0.1048	-0.5490	1.0672	0.2559	-1.0806	0.0099	0.0040	0.0020	0.0037	1781.28
	(0.0247)	(0.0831)	(0.0235)	(0.3565)	(1.6275)	(0.0023)	(0.0013)	(0.0004)	(0.0011)	
Levi Strauss& Co	0.3546	-1.3011	2.0732	1.1199	-4.1703	0.0121	0.0084	0.0086	0.0126	1384.73
	(0.1185)	(0.4681)	(0.0521)	(0.9313)	(4.1850)	(0.0014)	(0.0006)	(0.0003)	(0.0004)	
Liz Claiborne Inc	0.1083	-0.5485	1.1101	0.1255	-0.5585	0.0114	0.0041	0.0030	0.0045	1723.69
	(0.0387)	(0.1193)	(0.0279)	(0.3089)	(1.4217)	(0.0012)	(0.0002)	(0.0008)	(0.0012)	
L 3 Comms Corp	0.0481	-0.3363	1.3256	1.3465	-6.7043	0.0020	0.0015	0.0011	0.0016	2067.38
	(0.0176)	(0.0938)	(0.0825)	(1.4281)	(7.0238)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	
Liberty Media LLC	0.2999	-1.4040	1.9154	1.0746	-5.2911	0.0038	0.0026	0.0014	0.0021	1318.46
	(0.0456)	(0.2173)	(0.0825)	(1.2050)	(5.8394)	(0.0007)	(0.0006)	(0.0005)	(0.0006)	
Lockheed Martin Corp	0.3061	-1.7449	1.2978	1.1564	-7.7683	0.0004	0.0003	0.0003	0.0006	2744.71
	(0.0182)	(0.0990)	(0.0267)	(0.4941)	(3.4051)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Lowes Cos Inc	0.2022	-1.3154	1.4413	0.6528	-4.2990	0.0007	0.0004	0.0005	0.0008	2579.70
	(0.0151)	(0.0871)	(0.0380)	(0.5442)	(3.6775)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
LA Pac Corp	0.4924	-2.5747	1.9636	0.8099	-4.2027	0.0109	0.0031	0.0016	0.0023	1846.23
	(0.0581)	(0.2943)	(0.0604)	(0.6693)	(3.7334)	(0.0008)	(0.0003)	(0.0001)	(0.0003)	
Ltd Brands Inc	0.3674	-1.8878	1.7397	0.4293	-2.6522	0.0031	0.0017	0.0013	0.0018	2083.17
	(0.0238)	(0.1044)	(0.0280)	(0.4219)	(2.3803)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	
Loews Corp	0.0932	-0.6591	1.1756	0.5273	-2.9913	0.0008	0.0004	0.0003	0.0007	2625.15
	(0.0209)	(0.1063)	(0.0364)	(0.6218)	(3.7802)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	

Table 17: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
Southwest Airls Co	0.2696	-1.4491	1.4576	0.5670	-3.2588	0.0017	0.0010	0.0010	0.0019	2244.27
	(0.0137)	(0.0639)	(0.0283)	(0.3937)	(2.2349)	(0.0001)	(0.0001)	(0.0002)	(0.0004)	
Level 3 Comms Inc	0.2820	-0.5466	1.1696	0.7162	-1.6624	0.0500	0.0231	0.0097	0.0168	1046.44
	(0.0459)	(0.1426)	(0.0236)	(0.4166)	(1.1436)	(0.0034)	(0.0010)	(0.0011)	(0.0020)	
Macy s Inc	0.3467	-1.7179	1.5316	0.3915	-1.9712	0.0040	0.0028	0.0016	0.0021	1007.32
	(0.0300)	(0.1255)	(0.0389)	(0.5535)	(2.4179)	(0.0005)	(0.0013)	(0.0006)	(0.0004)	
Macy s Retail Hldgs Inc	0.4681	-2.5348	1.9162	0.6824	-3.5656	0.0037	0.0024	0.0016	0.0025	1007.92
	(0.0415)	(0.1759)	(0.0561)	(0.6466)	(3.2158)	(0.0008)	(0.0009)	(0.0005)	(0.0007)	
Marriott Intl Inc	0.0744	-0.5278	1.2556	0.4554	-2.5102	0.0023	0.0010	0.0012	0.0017	2209.41
	(0.0133)	(0.0488)	(0.0326)	(0.5233)	(2.7668)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	
Masco Corp	0.1628	-0.8225	1.1794	0.2071	-1.0791	0.0040	0.0021	0.0011	0.0021	2065.05
	(0.0214)	(0.0782)	(0.0229)	(0.3389)	(1.7111)	(0.0008)	(0.0005)	(0.0002)	(0.0005)	
MBIA Ins Corp	0.2481	-0.6600	0.9019	0.2484	-1.2527	0.0500	0.0499	0.0156	0.0486	707.68
	(0.0030)	(0.0090)	(0.0192)	(0.0865)	(0.5241)	(0.0020)	(0.0094)	(0.0031)	(0.0151)	
Mediacom LLC	0.0809	-0.2269	1.8526	2.4887	-8.5530	0.0132	0.0064	0.0027	0.0041	1575.52
	(0.0507)	(0.2253)	(0.1129)	(1.4816)	(5.8086)	(0.0018)	(0.0012)	(0.0004)	(0.0005)	
McDonalds Corp	0.2463	-1.4447	1.2379	1.0999	-7.4460	0.0005	0.0003	0.0004	0.0007	2713.24
	(0.0199)	(0.1148)	(0.0406)	(0.7092)	(4.9759)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
McKesson Corp	0.0699	-0.5476	1.2490	1.4056	-8.5987	0.0008	0.0005	0.0005	0.0010	2529.81
	(0.0247)	(0.1360)	(0.0616)	(1.1014)	(6.8834)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	
McClatchy Co	0.4999	-1.7718	1.7300	0.4999	-2.2716	0.0500	0.0500	0.0254	0.0500	163.67
	(0.0008)	(0.0000)	(0.0000)	(0.3572)	(1.9847)	(0.0022)	(0.0075)	(0.0057)	(0.0076)	
M D C Hldgs Inc	0.1658	-0.8841	1.1931	1.1359	-5.4721	0.0032	0.0020	0.0011	0.0021	2094.75
	(0.0293)	(0.1231)	(0.0549)	(1.0605)	(5.2864)	(0.0006)	(0.0005)	(0.0003)	(0.0006)	
Massey Engy Co	-0.1956	0.8124	1.0782	1.3063	-5.3275	0.0081	0.0043	0.0018	0.0033	1758.50
	(0.0263)	(0.1068)	(0.0465)	(1.0555)	(4.0977)	(0.0012)	(0.0006)	(0.0003)	(0.0005)	
MetLife Inc	0.1268	-0.7840	1.2834	0.2448	-1.4108	0.0054	0.0017	0.0008	0.0012	2141.33
	(0.0165)	(0.0701)	(0.0191)	(0.2899)	(1.5729)	(0.0006)	(0.0001)	(0.0001)	(0.0002)	
MGIC Invt Corp	0.1569	-1.0340	1.0933	0.2702	-1.0242	0.0240	0.0079	0.0042	0.0067	1501.08
	(0.0249)	(0.0953)	(0.0226)	(0.3183)	(1.3563)	(0.0054)	(0.0012)	(0.0011)	(0.0015)	
Mohawk Inds Inc	0.2231	-1.2283	1.5081	0.2427	-1.2161	0.0032	0.0017	0.0011	0.0020	2100.36
	(0.0192)	(0.0860)	(0.0364)	(0.4772)	(2.4950)	(0.0004)	(0.0003)	(0.0003)	(0.0005)	
Marsh& Mclennan Cos Inc	0.0818	-0.5567	1.1962	1.4415	-8.1109	0.0011	0.0005	0.0005	0.0011	2442.09
	(0.0152)	(0.0853)	(0.0495)	(1.0307)	(5.9874)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	
Altria Gp Inc	0.0512	-0.2618	0.8255	0.7941	-3.8792	0.0021	0.0011	0.0006	0.0012	2302.39
	(0.0121)	(0.0463)	(0.0145)	(0.4153)	(2.1147)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	
MeadWestvaco Corp	0.1426	-0.8596	1.4687	1.4194	-8.0657	0.0015	0.0011	0.0010	0.0019	2236.18
	(0.0217)	(0.1105)	(0.0581)	(0.8978)	(5.3682)	(0.0002)	(0.0002)	(0.0003)	(0.0005)	
Maytag Corp	-0.2081	0.8041	0.9242	0.6682	-3.3580	0.0019	0.0011	0.0011	0.0021	2178.86
	(0.0168)	(0.0671)	(0.0302)	(0.7156)	(3.4361)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	
NALCO Co	0.2111	-1.0010	2.0444	1.8092	-8.6745	0.0065	0.0034	0.0016	0.0025	1742.29
	(0.0637)	(0.3076)	(0.1101)	(1.3247)	(6.3103)	(0.0007)	(0.0004)	(0.0005)	(0.0006)	
NOVA Chems Corp	0.4968	-1.3175	2.7398	1.2106	-8.8939	0.0355	0.0222	0.0053	0.0164	1201.95
	(0.0640)	(0.1458)	(0.2308)	(1.7818)	(12.1569)	(0.0269)	(0.0661)	(0.0021)	(0.0349)	
Neiman Marcus Gp Inc	0.1197	-0.0707	2.1506	0.4574	-2.8717	0.0090	0.0046	0.0059	0.0101	1513.01
	(0.0210)	(0.0847)	(0.0431)	(0.4580)	(2.7361)	(0.0007)	(0.0004)	(0.0009)	(0.0017)	
Northrop Grumman Corp	0.2225	-1.3243	1.2717	0.8850	-5.6374	0.0005	0.0004	0.0003	0.0007	2682.48
	(0.0183)	(0.0985)	(0.0337)	(0.5662)	(3.7753)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
Natl Rural Utils Coop Fin Corp	0.0632	-0.5066	1.1991	0.6429	-3.6942	0.0027	0.0013	0.0006	0.0011	2291.74
	(0.0127)	(0.0521)	(0.0216)	(0.3793)	(2.2329)	(0.0006)	(0.0003)	(0.0001)	(0.0003)	
Norfolk Sthn Corp	0.2416	-1.3569	1.2249	0.9379	-5.9987	0.0006	0.0004	0.0004	0.0008	2637.50
	(0.0137)	(0.0780)	(0.0335)	(0.5844)	(3.6579)	(0.0001)	(0.0000)	(0.0001)	(0.0002)	
Newell Rubbermaid Inc	0.1934	-1.0954	1.3458	0.6977	-3.9744	0.0015	0.0010	0.0007	0.0011	2340.10
	(0.0184)	(0.0873)	(0.0286)	(0.4294)	(2.5564)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	
News America Inc	0.2901	-1.5411	1.3359	0.9694	-5.9470	0.0008	0.0006	0.0005	0.0009	2524.31
	(0.0154)	(0.0781)	(0.0233)	(0.3638)	(2.2261)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
NY Times Co	0.2927	-1.5868	1.6994	0.4388	-2.5104	0.0067	0.0022	0.0014	0.0020	1575.41
	(0.0297)	(0.1317)	(0.0428)	(0.5088)	(2.9556)	(0.0006)	(0.0003)	(0.0003)	(0.0003)	
Owens IL Inc	0.4173	-2.0648	2.1319	2.0877	-8.9606	0.0066	0.0029	0.0015	0.0024	1858.20
	(0.1012)	(0.5089)	(0.1352)	(1.5372)	(7.6506)	(0.0008)	(0.0004)	(0.0002)	(0.0003)	

Table 18: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
Olin Corp	0.3678	-2.0011	1.6870	1.5918	-8.9922	0.0019	0.0013	0.0012	0.0022	2178.43
	(0.0353)	(0.1819)	(0.0648)	(0.9556)	(5.4257)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	
Omnicom Gp Inc	0.1675	-1.0152	1.3307	0.4738	-2.8599	0.0010	0.0007	0.0006	0.0012	2435.90
	(0.0107)	(0.0516)	(0.0240)	(0.3526)	(2.1040)	(0.0000)	(0.0001)	(0.0001)	(0.0003)	
Pitney Bowes Inc	-0.1094	0.3399	1.1172	0.9171	-5.5117	0.0011	0.0007	0.0007	0.0011	2432.15
	(0.0189)	(0.0798)	(0.0455)	(1.0118)	(6.0438)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Pride Intl Inc	-0.0719	0.2340	1.2057	1.4577	-7.0069	0.0032	0.0020	0.0014	0.0024	2005.66
	(0.0254)	(0.1068)	(0.0538)	(1.0015)	(4.6927)	(0.0004)	(0.0003)	(0.0003)	(0.0005)	
Pfizer Inc	0.1114	-0.7989	1.1775	0.3444	-2.3318	0.0006	0.0004	0.0002	0.0004	2790.36
	(0.0213)	(0.1017)	(0.0229)	(0.4330)	(2.7544)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	
Progress Engy Inc	0.1966	-1.2126	1.3364	1.2126	-7.5575	0.0009	0.0006	0.0003	0.0006	2603.21
	(0.0250)	(0.1297)	(0.0363)	(0.6079)	(4.0374)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Parker Drilling Co	0.3224	-1.5656	2.0482	1.8599	-8.1276	0.0082	0.0042	0.0020	0.0025	1786.14
	(0.0536)	(0.2627)	(0.1120)	(1.3399)	(6.1605)	(0.0011)	(0.0008)	(0.0002)	(0.0003)	
PMI Gp Inc	-0.2105	0.1392	0.6479	0.2288	-0.6541	0.0293	0.0108	0.0072	0.0134	1346.73
	(0.0245)	(0.0551)	(0.0112)	(0.2606)	(0.7469)	(0.0042)	(0.0022)	(0.0027)	(0.0041)	
Polyone Corp	0.4144	-1.1050	2.3538	0.8674	-4.9110	0.0227	0.0084	0.0113	0.0191	1269.24
	(0.0282)	(0.0678)	(0.0623)	(0.5374)	(2.8253)	(0.0030)	(0.0013)	(0.0030)	(0.0096)	
Pioneer Nat Res Co	0.1769	-0.9539	1.5782	0.8621	-4.7398	0.0020	0.0015	0.0009	0.0019	2016.61
	(0.0194)	(0.0922)	(0.0347)	(0.4958)	(2.8360)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	
Qwest Cap Fdg Inc	0.0739	-0.3112	1.8238	0.9655	-4.5131	0.0067	0.0027	0.0020	0.0028	1813.46
	(0.0253)	(0.1170)	(0.0762)	(0.9002)	(4.1976)	(0.0005)	(0.0003)	(0.0005)	(0.0005)	
Ryder Sys Inc	0.1374	-0.9137	1.4254	0.6669	-3.9027	0.0018	0.0011	0.0010	0.0018	2237.64
	(0.0174)	(0.0782)	(0.0349)	(0.5912)	(3.3892)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	
Rite Aid Corp	0.2123	-0.3243	1.3077	0.4352	-1.4334	0.0500	0.0271	0.0460	0.0500	779.79
	(0.0149)	(0.0189)	(0.0247)	(0.3385)	(1.1573)	(0.0052)	(0.0079)	(0.0494)	(0.0279)	
Reynolds Amern Inc	0.2116	-1.0721	1.4072	0.7353	-3.4604	0.0024	0.0014	0.0010	0.0016	1929.13
	(0.0252)	(0.1166)	(0.0415)	(0.7491)	(3.7985)	(0.0005)	(0.0002)	(0.0002)	(0.0003)	
Royal Caribbean Cruises Ltd	0.1432	-0.6960	1.5180	0.7004	-3.2008	0.0093	0.0041	0.0045	0.0078	1622.30
	(0.0495)	(0.1919)	(0.0369)	(0.4990)	(2.4273)	(0.0011)	(0.0002)	(0.0006)	(0.0012)	
Radian Gp Inc	0.0628	-0.2070	1.2497	0.1646	-0.7366	0.0500	0.0225	0.0157	0.0301	1018.05
	(0.0219)	(0.0750)	(0.0254)	(0.2551)	(1.1716)	(0.0031)	(0.0053)	(0.0084)	(0.0141)	
Realogy Corp	0.4976	-1.2249	1.1408	0.4976	-1.8653	0.0500	0.0500	0.0164	0.0405	339.42
	(0.0024)	(0.0071)	(0.0132)	(0.1641)	(0.9934)	(0.0025)	(0.0075)	(0.0020)	(0.0082)	
Rio Tinto Alcan Inc	-0.0169	-0.1934	1.1045	0.7376	-4.1049	0.0016	0.0006	0.0005	0.0009	1076.80
	(0.0114)	(0.0485)	(0.0473)	(0.7242)	(3.7679)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	
Rohm& Haas Co	0.2473	-1.3902	1.3170	0.5822	-3.8235	0.0008	0.0006	0.0005	0.0010	2520.54
	(0.0123)	(0.0649)	(0.0263)	(0.4651)	(2.7958)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
RadioShack Corp	0.0168	-0.2059	1.3015	1.0171	-5.2634	0.0034	0.0020	0.0019	0.0031	1969.03
	(0.0109)	(0.0440)	(0.0264)	(0.5846)	(2.9815)	(0.0006)	(0.0005)	(0.0008)	(0.0010)	
Raytheon Co	0.3992	-2.2821	1.4883	1.1306	-7.4984	0.0005	0.0004	0.0003	0.0006	2687.15
	(0.0256)	(0.1350)	(0.0269)	(0.4859)	(3.4630)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	
Sprint Nextel Corp	0.1943	-0.9665	1.4977	0.3168	-1.6850	0.0084	0.0040	0.0017	0.0030	1401.36
	(0.0305)	(0.1161)	(0.0359)	(0.3716)	(1.7878)	(0.0010)	(0.0011)	(0.0005)	(0.0009)	
Sanmina SCI Corp	-0.1206	0.5652	1.3291	1.0247	-4.3910	0.0221	0.0109	0.0070	0.0087	1381.18
	(0.0575)	(0.2313)	(0.0295)	(0.5643)	(2.2416)	(0.0009)	(0.0009)	(0.0003)	(0.0006)	
Smithfield Foods Inc	0.1751	-0.8130	2.1335	0.6694	-3.2965	0.0098	0.0053	0.0030	0.0050	1641.13
	(0.0599)	(0.2712)	(0.0874)	(0.8638)	(4.3377)	(0.0010)	(0.0010)	(0.0006)	(0.0009)	
Istar Finl Inc	0.2166	-0.6479	0.9653	0.2166	-0.9076	0.0500	0.0500	0.0155	0.0467	717.91
	(0.0019)	(0.0070)	(0.0109)	(0.1104)	(0.5927)	(0.0033)	(0.0080)	(0.0021)	(0.0152)	
SUNGARD DATA Sys INC	0.1702	-0.5949	2.1450	1.4947	-6.8839	0.0084	0.0046	0.0026	0.0039	1283.49
	(0.0815)	(0.3641)	(0.1479)	(1.5398)	(7.4240)	(0.0012)	(0.0009)	(0.0002)	(0.0004)	
SEARS ROEBUCK Accep CORP	0.3476	-1.7200	1.7146	0.5482	-2.8828	0.0133	0.0044	0.0033	0.0053	1650.78
	(0.0348)	(0.1503)	(0.0314)	(0.5026)	(2.4640)	(0.0049)	(0.0011)	(0.0007)	(0.0025)	
Sherwin Williams Co	0.2773	-1.6757	1.4973	1.2509	-8.1373	0.0008	0.0006	0.0005	0.0009	2525.54
	(0.0214)	(0.1105)	(0.0358)	(0.6207)	(4.0102)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Saks Inc	0.0828	-0.0416	2.1273	0.8764	-4.7556	0.0097	0.0051	0.0052	0.0093	1523.80
	(0.0242)	(0.0922)	(0.0376)	(0.5671)	(2.6050)	(0.0008)	(0.0005)	(0.0010)	(0.0020)	
Sara Lee Corp	-0.1343	0.4933	1.1897	1.3388	-7.9543	0.0012	0.0008	0.0009	0.0015	2343.19
	(0.0321)	(0.1398)	(0.0729)	(1.3984)	(8.6115)	(0.0002)	(0.0002)	(0.0004)	(0.0006)	

Table 19: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
SLM Corp	0.1284	-0.7490	1.2649	0.1916	-0.9462	0.0322	0.0076	0.0043	0.0077	1475.99
	(0.0204)	(0.0831)	(0.0174)	(0.3618)	(1.2721)	(0.0021)	(0.0009)	(0.0016)	(0.0025)	
Std Pac Corp	0.1208	-0.5563	1.9430	0.7952	-3.5186	0.0125	0.0059	0.0045	0.0076	1473.61
	(0.0624)	(0.2710)	(0.0551)	(0.7228)	(3.1227)	(0.0017)	(0.0009)	(0.0008)	(0.0015)	
Simon Ppty Gp L P	0.0669	-0.5445	1.2392	0.4500	-2.4208	0.0022	0.0013	0.0006	0.0012	2255.69
	(0.0105)	(0.0365)	(0.0224)	(0.3734)	(1.9552)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Staples Inc	0.0894	-0.6702	1.3239	0.8115	-4.6267	0.0014	0.0008	0.0009	0.0013	2338.84
	(0.0116)	(0.0471)	(0.0308)	(0.5307)	(2.9023)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Sempra Engy	0.2383	-1.3899	1.3339	1.3732	-8.3780	0.0012	0.0007	0.0004	0.0007	2512.59
	(0.0162)	(0.0840)	(0.0281)	(0.4894)	(3.0499)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Constellation Brands Inc	-0.1108	0.4659	1.2827	1.8668	-8.7239	0.0035	0.0030	0.0016	0.0020	1950.08
	(0.0213)	(0.0954)	(0.0600)	(1.1227)	(5.5133)	(0.0004)	(0.0005)	(0.0002)	(0.0002)	
SUPERVALU INC	-0.1260	0.4782	0.9706	0.6522	-2.8029	0.0059	0.0033	0.0018	0.0029	1859.15
	(0.0246)	(0.0994)	(0.0272)	(0.6242)	(2.8105)	(0.0012)	(0.0009)	(0.0003)	(0.0005)	
New Albertson s Inc	-0.2762	0.8915	0.5175	0.7723	-2.6187	0.0035	0.0016	0.0014	0.0017	837.56
	(0.0432)	(0.1381)	(0.0295)	(1.4004)	(4.5162)	(0.0007)	(0.0004)	(0.0006)	(0.0005)	
Safeway Inc	0.1057	-0.6732	1.2836	1.3847	-7.8115	0.0015	0.0010	0.0010	0.0017	2289.09
	(0.0276)	(0.1387)	(0.0745)	(1.3129)	(7.8307)	(0.0003)	(0.0002)	(0.0003)	(0.0004)	
AT&T Corp.	-0.2486	1.0793	1.0211	0.8983	-5.1989	0.0015	0.0008	0.0007	0.0012	2371.36
	(0.0159)	(0.0664)	(0.0397)	(0.7941)	(4.4797)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Target Corp	0.1684	-1.0901	1.3370	0.6207	-4.0201	0.0006	0.0004	0.0006	0.0009	2575.80
	(0.0096)	(0.0505)	(0.0309)	(0.4658)	(2.9614)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	
Tenet Healthcare Corp	0.2926	-1.0457	2.4060	1.9295	-8.8058	0.0135	0.0056	0.0035	0.0052	1576.16
	(0.1052)	(0.4923)	(0.1215)	(1.2397)	(5.6581)	(0.0012)	(0.0006)	(0.0009)	(0.0015)	
Temple Inland Inc	0.2361	-1.3095	1.6023	0.9048	-4.8858	0.0037	0.0022	0.0012	0.0020	2039.74
	(0.0169)	(0.0796)	(0.0307)	(0.4298)	(2.3877)	(0.0007)	(0.0006)	(0.0003)	(0.0004)	
TJX Cos Inc	0.3014	-1.7998	1.5131	0.8681	-5.7841	0.0007	0.0006	0.0006	0.0011	2510.15
	(0.0185)	(0.1042)	(0.0381)	(0.5705)	(3.7577)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	
Toll Bros Inc	0.4737	-2.4775	1.6492	1.0172	-5.0411	0.0045	0.0025	0.0014	0.0026	1990.60
	(0.0390)	(0.1852)	(0.0516)	(0.6934)	(3.7234)	(0.0009)	(0.0008)	(0.0005)	(0.0010)	
TOYS R US INC	0.5000	-1.3729	2.5115	0.6411	-3.6709	0.0104	0.0050	0.0096	0.0191	1383.98
	(0.0262)	(0.0857)	(0.0609)	(0.6824)	(3.6968)	(0.0006)	(0.0002)	(0.0040)	(0.0066)	
Tribune Co	0.3503	-0.9749	1.1555	0.3503	-1.8321	0.0500	0.0500	0.0145	0.0449	539.15
	(0.0000)	(0.0000)	(0.0000)	(0.2015)	(1.3277)	(0.0132)	(0.0118)	(0.0015)	(0.0062)	
TRW Automotive Inc	0.4999	-1.9817	2.4820	0.8520	-5.3364	0.0303	0.0121	0.0055	0.0130	1283.07
	(0.1176)	(0.5437)	(0.0858)	(0.7455)	(4.3598)	(0.0079)	(0.0041)	(0.0014)	(0.0054)	
Sabre Hldgs Corp	0.4079	-1.1347	2.3396	0.4592	-3.0521	0.0131	0.0083	0.0105	0.0207	1296.63
	(0.0315)	(0.1285)	(0.0404)	(0.4883)	(2.7363)	(0.0007)	(0.0005)	(0.0065)	(0.0143)	
Tyson Foods Inc	0.1626	-0.8783	1.3756	1.1180	-5.7386	0.0028	0.0016	0.0012	0.0018	2096.25
	(0.0150)	(0.0693)	(0.0363)	(0.5826)	(3.0866)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	
Tesoro Corp	-0.0666	0.2673	1.5772	0.8453	-4.3252	0.0063	0.0038	0.0014	0.0020	1676.14
	(0.0242)	(0.1122)	(0.0610)	(0.8675)	(4.5044)	(0.0011)	(0.0008)	(0.0003)	(0.0003)	
Time Warner Inc	0.2413	-1.3530	1.3813	1.1016	-6.6260	0.0013	0.0007	0.0006	0.0011	2415.82
	(0.0217)	(0.1082)	(0.0333)	(0.5290)	(3.3561)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
TIME WARNER CABLE INC	0.0855	-0.5836	1.3160	1.5568	-7.7734	0.0023	0.0010	0.0006	0.0011	1167.23
	(0.0224)	(0.1011)	(0.0667)	(1.5608)	(7.7057)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	
Historic TW Inc	0.1761	-0.9727	1.3197	0.5961	-3.5277	0.0005	0.0005	0.0004	0.0007	1339.67
	(0.0324)	(0.1759)	(0.0633)	(0.7845)	(4.9857)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Textron Finl Corp	0.1332	-0.7960	1.2089	0.1565	-0.8393	0.0108	0.0032	0.0010	0.0018	1972.85
	(0.0284)	(0.1205)	(0.0208)	(0.2486)	(1.2974)	(0.0037)	(0.0013)	(0.0002)	(0.0004)	
Unvl Health Svcs Inc	-0.0873	0.2718	1.1242	0.8430	-4.3988	0.0024	0.0015	0.0010	0.0018	2158.26
	(0.0157)	(0.0645)	(0.0475)	(1.0121)	(5.1614)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	
Unisys Corp	0.3751	-1.0304	1.1464	0.3751	-1.5284	0.0500	0.0379	0.0094	0.0296	965.39
	(0.0077)	(0.0144)	(0.0171)	(0.1989)	(0.9410)	(0.0160)	(0.0221)	(0.0005)	(0.0025)	
UnitedHealth Gp Inc	0.0156	-0.2524	1.1127	0.4260	-2.4167	0.0014	0.0009	0.0004	0.0008	2438.63
	(0.0070)	(0.0324)	(0.0203)	(0.4590)	(2.4125)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Un Pac Corp	0.2771	-1.5890	1.3466	1.2241	-7.8437	0.0007	0.0004	0.0004	0.0008	2574.73
	(0.0182)	(0.1047)	(0.0386)	(0.6664)	(4.2131)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Utd Parcel Svc Inc	0.1007	-0.7331	1.1647	0.5520	-3.8209	0.0004	0.0003	0.0003	0.0006	2803.48
	(0.0118)	(0.0552)	(0.0213)	(0.4762)	(3.0253)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	

Table 20: Parameters

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(3)$	$\sigma(7)$	$\sigma(10)$	LogLk
Utd Rents North Amer Inc	0.0150	-0.0213	1.7813	1.1297	-4.7314	0.0106	0.0060	0.0032	0.0048	1536.77
	(0.0136)	(0.0570)	(0.1035)	(1.3049)	(5.3629)	(0.0011)	(0.0007)	(0.0006)	(0.0008)	
Univision Comms Inc	0.2420	-0.4434	1.6140	0.2433	-1.3102	0.0500	0.0128	0.0445	0.0500	669.25
	(0.0104)	(0.0123)	(0.0588)	(0.2600)	(1.2033)	(0.0140)	(0.0021)	(0.0223)	(0.0138)	
Visteon Corp	-1.9618	2.3421	2.7983	8.9645	-8.8320	0.0500	0.0499	0.0493	0.0500	-17822.77
	(0.0000)	(0.0003)	(0.0000)	(0.5387)	(0.7112)	(0.0002)	(0.0004)	(0.0008)	(0.0001)	
Viacom	0.2311	-1.3051	1.5153	1.1021	-6.5395	0.0019	0.0009	0.0009	0.0017	1486.24
	(0.0215)	(0.1033)	(0.0358)	(0.6412)	(3.5298)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	
Valero Energy Corp	0.0657	-0.4105	1.1198	0.4209	-2.2058	0.0027	0.0015	0.0007	0.0012	1714.07
	(0.0158)	(0.0624)	(0.0365)	(0.6062)	(3.1914)	(0.0007)	(0.0005)	(0.0001)	(0.0002)	
Vornado Rlty LP	0.1422	-1.0665	1.6062	0.7019	-3.9208	0.0026	0.0013	0.0008	0.0010	2168.98
	(0.0165)	(0.0769)	(0.0317)	(0.5161)	(2.5154)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Verizon Comms Inc	0.1535	-1.0032	1.4116	0.9594	-6.0241	0.0011	0.0006	0.0006	0.0010	1482.91
	(0.0221)	(0.1155)	(0.0421)	(0.8398)	(5.2180)	(0.0002)	(0.0001)	(0.0002)	(0.0004)	
Wendys Intl Inc	0.0341	-0.2761	1.3658	0.5523	-2.9306	0.0037	0.0022	0.0019	0.0031	1934.99
	(0.0213)	(0.0939)	(0.0388)	(0.7143)	(3.8860)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	
Wells Fargo& Co	0.1826	-1.1677	1.2527	0.3595	-2.2481	0.0019	0.0010	0.0004	0.0006	2473.73
	(0.0157)	(0.0749)	(0.0198)	(0.3108)	(1.8631)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	
Whirlpool Corp	0.2698	-1.5210	1.5747	0.4820	-2.9053	0.0020	0.0013	0.0010	0.0017	2190.07
	(0.0130)	(0.0694)	(0.0351)	(0.4796)	(3.0132)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	
Windstream Corp	-0.0257	0.0823	1.5175	1.5435	-7.5162	0.0031	0.0025	0.0019	0.0030	1256.88
	(0.0298)	(0.1382)	(0.0904)	(1.4559)	(7.1688)	(0.0005)	(0.0006)	(0.0007)	(0.0009)	
WA Mut Inc	0.1040	-0.6225	2.1295	0.1589	-0.5198	0.0185	0.0030	0.0007	0.0016	133.12
	(0.0393)	(0.1905)	(0.0760)	(0.6095)	(2.4070)	(0.0025)	(0.0002)	(0.0000)	(0.0002)	
Wal Mart Stores Inc	0.1823	-1.1401	1.1804	0.3513	-2.2995	0.0004	0.0003	0.0003	0.0005	2790.27
	(0.0120)	(0.0630)	(0.0267)	(0.3984)	(2.7025)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	
Weyerhaeuser Co	0.1710	-0.9862	1.4904	0.6254	-3.5485	0.0020	0.0013	0.0010	0.0019	2186.52
	(0.0225)	(0.1100)	(0.0433)	(0.5818)	(3.4968)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	
NRG Energy Inc	0.0038	0.0859	1.8139	1.2872	-6.2735	0.0078	0.0049	0.0017	0.0024	1565.38
	(0.0079)	(0.0370)	(0.0775)	(1.0819)	(5.2321)	(0.0009)	(0.0006)	(0.0003)	(0.0003)	
Xerox Corp	0.3028	-1.5989	1.6059	0.7659	-3.8587	0.0023	0.0013	0.0007	0.0014	2190.93
	(0.0189)	(0.0910)	(0.0349)	(0.4793)	(2.6753)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	
XTO Engy Inc	0.1018	-0.6255	1.1107	0.6435	-3.7051	0.0009	0.0004	0.0005	0.0009	2524.18
	(0.0075)	(0.0381)	(0.0305)	(0.5305)	(2.9453)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	
TRW Automotive Inc	0.4999	-1.9817	2.4820	0.8520	-5.3364	0.0303	0.0121	0.0055	0.0130	1283.07
	(0.1176)	(0.5437)	(0.0858)	(0.7455)	(4.3598)	(0.0079)	(0.0041)	(0.0014)	(0.0054)	
Sabre Hldgs Corp	0.4079	-1.1347	2.3396	0.4592	-3.0521	0.0131	0.0083	0.0105	0.0207	1296.63
	(0.0315)	(0.1285)	(0.0404)	(0.4883)	(2.7363)	(0.0007)	(0.0005)	(0.0065)	(0.0143)	
Tyson Foods Inc	0.1626	-0.8783	1.3756	1.1180	-5.7386	0.0028	0.0016	0.0012	0.0018	2096.25
	(0.0150)	(0.0693)	(0.0363)	(0.5826)	(3.0866)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	
Tesoro Corp	-0.0666	0.2673	1.5772	0.8453	-4.3252	0.0063	0.0038	0.0014	0.0020	1676.14
	(0.0242)	(0.1122)	(0.0610)	(0.8675)	(4.5044)	(0.0011)	(0.0008)	(0.0003)	(0.0003)	
Time Warner Inc	0.2413	-1.3530	1.3813	1.1016	-6.6260	0.0013	0.0007	0.0006	0.0011	2415.82
	(0.0217)	(0.1082)	(0.0333)	(0.5290)	(3.3561)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
TIME WARNER CABLE INC	0.0855	-0.5836	1.3160	1.5568	-7.7734	0.0023	0.0010	0.0006	0.0011	1167.23
	(0.0224)	(0.1011)	(0.0667)	(1.5608)	(7.7057)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	
Historic TW Inc	0.1761	-0.9727	1.3197	0.5961	-3.5277	0.0005	0.0005	0.0004	0.0007	1339.67
	(0.0324)	(0.1759)	(0.0633)	(0.7845)	(4.9857)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Textron Finl Corp	0.1332	-0.7960	1.2089	0.1565	-0.8393	0.0108	0.0032	0.0010	0.0018	1972.85
	(0.0284)	(0.1205)	(0.0208)	(0.2486)	(1.2974)	(0.0037)	(0.0013)	(0.0002)	(0.0004)	
Unvl Health Svcs Inc	-0.0873	0.2718	1.1242	0.8430	-4.3988	0.0024	0.0015	0.0010	0.0018	2158.26
	(0.0157)	(0.0645)	(0.0475)	(1.0121)	(5.1614)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	
Unisys Corp	0.3751	-1.0304	1.1464	0.3751	-1.5284	0.0500	0.0379	0.0094	0.0296	965.39
	(0.0077)	(0.0144)	(0.0171)	(0.1989)	(0.9410)	(0.0160)	(0.0221)	(0.0005)	(0.0025)	
UnitedHealth Gp Inc	0.0156	-0.2524	1.1127	0.4260	-2.4167	0.0014	0.0009	0.0004	0.0008	2438.63
	(0.0070)	(0.0324)	(0.0203)	(0.4590)	(2.4125)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Un Pac Corp	0.2771	-1.5890	1.3466	1.2241	-7.8437	0.0007	0.0004	0.0004	0.0008	2574.73
	(0.0182)	(0.1047)	(0.0386)	(0.6664)	(4.2131)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	
Utd Parcel Svc Inc	0.1007	-0.7331	1.1647	0.5520	-3.8209	0.0004	0.0003	0.0003	0.0006	2803.48
	(0.0118)	(0.0552)	(0.0213)	(0.4762)	(3.0253)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	

Chapter 3

Market-Wide Liquidity in Credit Default Swap Spreads

Abstract

This paper analyzes the importance of market-wide illiquidity of the CDS, equity, and corporate bond markets on changes of CDS spreads of credit quality portfolios for five alternative maturities. Illiquidity CDS betas across credit quality portfolios and maturities are positive and statistically significant. Our evidence is robust to alternative market-wide measures of illiquidity from different financial markets, and other macroeconomic control measures. Low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. There is also evidence of flight-to-liquidity during stress periods, at least at short horizons.

1 Introduction

It is generally accepted that credit default swap spreads (CDS spreads) can be decomposed into the expected loss, a default risk premium, a liquidity risk premium related to the impact of trades on the spread and the adverse selection effect associated with the asymmetric information between the CDS sellers and buyers, and the correlation-induced components.[1] However, initial papers on CDS spreads have considered the spreads as a pure measure of creditworthiness of a company. The existence of a potentially important liquidity component is originally suggested by the evidence reported by Blanco, Brennan, and Marsh (2005), and Berndt, Duglas, Duffie, Ferguson, and Schranz (2008). Indeed, Blanco et al. (2005) report average CDS spreads larger than the underlying corporate bond yield spreads for most of the entities on their sample, and Berndt et al. (2008) find that, on average, a significant component of the spreads cannot be explained by default risk measured by the Moody's KMV's expected default frequencies.

These papers motivate a relatively large literature about the importance of the liquidity component on the CDS spreads.[2] The empirical evidence clearly supports the presence of a liquidity component of CDS spreads independently of credit quality, maturity and type of underlying. This is the case despite the large variety of econometric methodologies and theoretical models employed in the estimation. For example, Chen et al. (2005), Chen et al. (2010), and Buhler and Trapp (2009) employ the intensity framework for pricing CDS spreads proposed by Duffie and Singleton (2003), and Pan and Singleton (2008), where liquidity enters the picture as a further spread, or intensity, over and above the risk neutral arrival rate of a credit event component. On the other hand, Bongaerts et al. (2011) propose an equilibrium derivative pricing model with liquidity effects in which the zero net-supply feature of the derivative market generates very different liquidity effects than the liquidity pricing model of Acharya and Pedersen (2005). They find that only compensation for expected liquidity is significant with higher expected liquidity being associated with higher expected returns for the protection sellers. As pointed out by Brigo et al. (2010) this finding is contrary to Chen et al. (2005), and Chen et al. (2010) that found protection buyers to obtain the liquidity premium. In any case, not only these theoretically-based papers, but also other empirical-based literature mentioned above concludes that CDS spreads cannot be assumed to be pure measures of credit risk. CDS liquidity seems to be significantly priced in CDS spreads.

However, most papers analyze the importance of liquidity at the individual level.[3] This is surprising

[1] See Buhler and Trapp (2009), Jarrow (2011), and Bongaerts, Jong, and Driessen (2011), among others.

[2] See Chen, Cheng, and Wu (2005), Tang and Yan (2008), Chen, Fabozzi, and Sverdlove (2010), Buhler and Trapp (2009), Brigo, Predescu, and Capponi (2010), Pires, Perreira, and Martins (2010), Bongaerts et al. (2011), and Coro, Dufour, and Varotto (2012).

[3] An important exception is the paper by Coro et al. (2012) who employ European CDS data from GFI Group and Bloomberg that

given the available evidence from the corporate and sovereign bond markets. Xing, Zhang, and Zhou (2007) document a strong commonality in individual bond liquidity changes after controlling for both bond specific determinants, such as price and volatility, and macroeconomic state variables. They find that the covariance of a bond's liquidity with respect to market liquidity shocks is a significant risk factor in determining the yield spread. More recently, Acharya, Amihud, and Bharath (2010) report that during stress periods, liquidity risk is a significant factor in affecting corporate bond prices, especially of low-rated bonds, and Panyanukul (2009) finds that liquidity risk is a priced factor in explaining sovereign bond returns. As in the previous paper, this is especially the case during the period 2007 to 2009. This research suggests a strong conditional component of market-wide liquidity effects in both corporate and sovereign bond markets.

This paper contributes to the literature by analyzing market-wide liquidity in the CDS market. We study thoroughly the impact of illiquidity on CDS spreads on an aggregate level. We first show that, for a given maturity and credit rating, there is a strong commonality in the liquidity of CDS contracts. Then, we show that market-wide illiquidity is a powerful determinant of CDS spreads. There is a consistently positive and significant relation between CDS spreads and market-wide illiquidity changes across all maturities and credit qualities. Moreover, this relation is stronger during stress periods. Finally, there is a monotonic relationship between sensitivity to market-wide changes of liquidity and credit ratings, being this sensitivity stronger for high yield underlyings. Indeed, aggregate illiquidity risk seems to be a more important factor than credit risk in the CDS market. This conclusion is also supported by a significant flight-to-liquidity given the time-varying nature of liquidity risk embedded in CDS spreads. This is particularly important at the shortest maturities. Crisis episodes reflect short-term flight-to-liquidity but not flight-to-credit quality.

The remainder of the paper is organized as follows. Section 2 describes the data employed in the analysis and the methodology for constructing CDS portfolios. Section 3 presents the relation between CDS spread changes and market-wide variables for portfolios sorted by maturity and credit quality. Section 4 performs the flight-to-liquidity and flight-to-quality analysis, and Section 5 concludes with summary and final remarks.

2 Data, Credit-quality-sorted Portfolios, and Aggregate Variables

We obtain data on CDS spreads from Markit Group Ltd. We consider corporate (non-sovereign) CDS names incorporated in North America, which are or have been part of the CDX North America index. We further restrict our sample to CDS contracts, which are (i) denominated in US dollars (ii) are written on senior

covers the period from January 1, 2006 to July 31, 2009.

unsecured debt of companies, and (iii) incorporate the modified restructuring clause as a credit event. These are the typical terms that a CDS contract trades on in North America. In our analysis, we consider the time period from January 2004 to April 2011. Additionally, for each CDS name we use the spreads with 1-, 3-, 5-, 7-, and 10 year maturities. Finally, our analysis deals with monthly CDS spreads. In particular, we construct monthly CDS spreads for a given name and maturity by taking the last non-missing daily CDS spread for each month. The above criteria leave us with an overall sample of 284 CDS names, which amount to 21,623 issuer-month observations.

Table 1 provides the distribution of CDS names in our sample by sector and rating group. The reported rating is the resulting average of Moody's and S&P ratings that are adjusted to the seniority of the instrument and are rounded not to include the plus and minus levels. Market uses 10-sector ICB classification and adds one additional category for Government. Those sectors are Financial, Oil & Gas, Basic Materials, Industrial, Consumer Goods, Consumer Services, Health Care, Telecommunications, Utilities, Technology and Government. Nearly 52% of the CDS contracts in our database are written on the debt of investment grade companies, whereas the share of CDS contracts written on the debt of high-yield companies is 48%. There are 4 industries represented individually by more than 10% of the total number of contracts. These are CDS contracts written on the debt of companies from the Consumer Services, Financial, Consumer Goods, and Industrial sectors. These four sectors cover around 65% of our sample.

[INSERT TABLE 1 ABOUT HERE]

Figure 1 display the time series of aggregate monthly CDS spreads by maturity. This series is calculated by taking the cross-sectional average of individual CDS spreads for each month and maturity. We observe that CDS spreads of all maturities are relatively stable before mid 2007. Afterwards, there is a sharp increase in CDS spreads up to the beginning of 2009. The drastic increase of mid 2007 is associated with the burst of the housing bubble in the US around August 2007, and the associated losses on subprime mortgage asset backed securities, collateralized debt obligation bonds, and CDS on the asset backed holdings. When these financial securities lost value due to the housing market crash, financial institutions using these products did not have enough capital to respond to the enormous losses realized. Specifically, the upward sloping trend of CDS spread time series is followed by a series of credit events, such as the collapse of Lehman Brothers, the bailout of AIG group and the federal takeover of Fannie Mae and Freddie Mac in September 2008.[4] The

[4]See Jarrow (2011) for an overall discussion on the CDS market and the website of Federal Reserve of St. Louis for a detailed timeline of the credit events associated with the subprime financial crisis (http://timeline.stlouisfed.org/index.cfm?p=timeline).

slope of the term structure of CDS spreads is mostly positive, so that the spreads of short maturity horizons tend to be lower than the spreads of longer horizons. However, Figure 1 also shows that from mid 2008 till mid 2009 the CDS spreads with short-term maturity are higher than CDS spreads with long-term maturity. The inversion of the slope of the term structure during stress periods has also been documented by Pan and Singleton (2008) for some emerging countries during periods of financial or political crisis. It is important to point out that the inversion of the slope is perfectly monotonic.[5]

[INSERT FIGURE 1 ABOUT HERE]

2.1 Credit-quality-sorted Portfolios of CDS spreads

To assess the impact of market-wide illiquidity on CDS spreads, we construct credit-quality-sorted portfolios. In all subsequent sections we perform our regression analysis based on the CDS spreads of these credit-quality-sorted portfolios.

For a given maturity (1-, 3-, 5-, 7-, and 10 year horizons), we classify all CDS spreads according to the credit rating of the underlying asset. To have enough observations in each portfolio, we form 4 credit-quality-sorted portfolios of CDS spreads: AAA to A-, BBB+ to BBB-, BB+ to BB-, and B+ to D. We equally weight CDS spreads in each portfolio. To construct these four portfolios, first we obtain data on corporate credit ratings of the CDS names in our database. More specifically, we download this data from Thomson Reuters 3000 Xtra. Then, for each CDS name we can have data on credit rating assigned by S&P, Fitch or Moody's. In addition, we have detailed data on credit ratings for different categories of a debt of a particular company, such as long-term issuer rating, short-term issuer rating, issuer outlook, rating on debt in local currency, etc. When constructing our portfolios, we employ only the long-term issuer rating assigned by S&P, Fitch and Moody's. We have therefore to obtain a monthly time series of composite credit ratings for each CDS using three agencies. In order to construct this series, we take the previously assigned credit rating by a particular agency and apply it to all months up to the next month the agency issues a new rating. For instance, the long-term issuer rating assigned by S&P to Cox Communications Inc. was BBB for August 2008, and BBB- in December 2008. Hence, we take the BBB to be the issuer credit rating assigned by S&P for all four months

[5] Schneider, Sogner, and Veza (2009) point out that the one-year CDS spread exhibits time-varying behavior higher-maturity spreads do not share. They presume that investment funds primarily use the 1-year CDS spreads to express their views on the creditworthiness of CDS names. Hence, they argue the economic driver behind the unique pattern in 1-year spreads is a supply-and-demand premium induced by such large traders. It should be pointed out however that the pattern shown in Figure 1 is the complete and monotonic inversion of the slope of the term structure. This implies that this phenomenon is not uniquely related to the shortest maturity CDS spreads.

from August 2008 to November 2008. We construct the composite rating measure by taking the average of at most three ratings on long-term issuers assigned by the three credit rating agencies to a CDS name for a given month. To calculate the average rating of a CDS name, we transform the long-term issuer ratings from the letter scale to numerical, by taking the letter rating designation of S&P as a common base (AAA = 1, AA+ = 2, ..., D = 22). As Moody's uses a different scale than S&P and Fitch, beforehand we translate the rating tier of Moody's to the scale equivalent to S&P's by equating the categories as Aaa = AAA, Baa1 = BBB+, etc. Finally, we obtain the composite rating assigned to a CDS name for a given month by transforming the averaged numerical rating (rounded to the nearest integer) to the letter scale used by S&P. This procedure leaves us with 4 equally-weighted portfolios of CDS spreads for a given maturity.

Table 2 reports the summary statistics of these portfolios. Portfolio CDS spreads increase on average as the portfolio maturity increases. This holds for all CDS portfolios. This is consistent with a (average) positive slope of the term structure of CDS spreads. Simultaneously, holding the maturity constant, the portfolio CDS spreads increase as the credit quality of the corresponding CDS portfolio deteriorates. The same observations hold for the median of portfolio CDS spreads. On the other hand, the standard deviation of portfolio CDS spreads grows as the maturity of the corresponding CDS portfolio decreases. In other words, for a given credit-quality-sorted portfolio of CDS, spreads with short-term maturity are more volatile than CDS spreads with long-term maturity. And, for a given maturity, the volatility of the spreads increases with the deterioration of credit quality.

[INSERT TABLE 2 ABOUT HERE]

Figure 2 plots the time series of portfolio CDS spreads with 5 year maturity for alternative credit ratings. The dynamics of the spreads across different rating categories reinforce our previous observation that the portfolio CDS spreads are higher as the credit quality of the corresponding portfolio declines. We also observe that the portfolio CDS spreads increase substantially after the start of the financial crisis of August 2007, and this is especially true for lowest rating portfolio.

[INSERT FIGURE 2 ABOUT HERE]

2.2 Aggregate illiquidity Measures

We employ two aggregate measures of illiquidity for the CDS market, which are based on the absolute bid-ask spreads of CDS names and on the gamma measures of illiquidity of Roll (1984), and Bao, Pan, and

Wang (2011). We estimate the aggregate bid-ask spread measure of illiquidity for the CDS market by taking the cross-sectional average of absolute bid-ask spreads of CDS names per month. We use absolute (rather than relative) bid-ask spreads as they are already a proportional measure and, therefore, they do not need to be scaled by the average of CDS bid and ask quotes.[6] As in the case of CDS spreads, we construct the monthly absolute bid-ask spread of a CDS name by taking the last non-missing daily absolute bid-ask spread for each month. Additionally, we obtain the aggregate bid-ask spread measures of illiquidity for maturities of one, three, five, seven, and ten years. Data on CDS bid-ask spreads are taken from CMA Datastream and is available from January 1, 2004 till September 30, 2010.

In the spirit of Bao et al. (2011), we also calculate the individual measure of gamma illiquidity for a CDS name i with T year maturity as,

$$\gamma_i(T) \quad = \quad cov\left(r_t^{cds_i}(T), r_{t+1}^{cds_i}(T)\right) \tag{1}$$

where $r_t^{cds_i}(T)$ is the CDS return of name i with T year maturity.[7] We calculate this measure for each CDS contract and maturity on monthly basis. In doing so, we impose the restriction that at least 10 observations of $r_t^{cds_i}(T)$ are available for each CDS name within each month.[8] To calculate daily CDS returns, we follow Berndt and Obreja (2010). In particular, the CDS return is given by,

$$r_t^{CDS}(T) = -\Delta CDS_t(T) \times A_t(T) \tag{2}$$

where

$$A_t(T) = \frac{1}{4}\sum_{s=1}^{4T} \delta(t, s/4) q(t, s/4)$$

and $\Delta CDS_t(T)$ is the daily change in CDS spreads with T year maturity, $\delta(t,s)$ denotes the risk neutral discount factor for day t and time period s, and $q(t,s)$ is the risk neutral survival probability of the CDS name over the future time period s. To calculate the risk neutral discount factors, we bootstrap the risk free interest rates from the US LIBOR interest rate term structure with 3-, 6-, 9-, and 12-month maturities augmented by

[6]See Pires et al. (2010) for a formal argument.

[7]The formula for gamma illiquidity for bonds in Bao et al. (2011) is defined as the negative of the covariance between consecutive bond price changes. As discussed by Roll (1984) in the context of stock returns, the reason for the negative sign is due to the fact that bond price returns exhibit negative serial correlation. However, CDS returns by construction approximate yield changes of the underlying bond. As pointed out by Blanco et al. (2005), among others, the CDS spread should be approximately equal to the bond yield minus the risk free rate. As it is well known, bond yield changes and bond returns are inversely related.

[8]We remove the CDS returns that fall outside the 5th and 95th percentile range of their distribution for each day and maturity.

the term structure of IRS swap spreads with 2-, 3-, 4-, 5-, 7-, and 10-year maturities. To calculate the risk neutral survival probabilities we use the approximation derived by Berndt and Obreja (2010):

$$q(t,s,\lambda) = e^{-\lambda(t-s)} \tag{3}$$

where

$$\lambda = 4\log\left(1+\frac{CDS_t(T)}{4(1-R)}\right)$$

Finally, to estimate the aggregate gamma measure of illiquidity for the CDS market, we take the cross-sectional mean of individual gamma measures of illiquidity of CDS names for each month and maturity.

To control for the illiquidity of other market, and the potential spillovers from bond and stock markets to the CDS market, we also employ the aggregate illiquidity measures for the stock and bond markets suggested by Amihud (2002). We calculate the individual Amihud ratio for each stock trading in the US market as,[9]

$$ILLIQ_t^i = \frac{1}{D_t^i}\sum_{d=1}^{D_t^i}\frac{|R_{td}^i|}{V_{td}^i} \tag{4}$$

where D_t^i is the number of days for which data is available for stock i in month t, R_{td}^i is the return on stock i on day d in month t, and V_{td}^i is the trading volume (in US dollars) for stock i on day d in month t. We obtain the aggregate Amihud ratio for the US stock market by taking the cross-sectional average of individual Amihud ratios for each month. Finally, we estimate the aggregate measure of illiquidity (*ILS*) for the US stock market by taking the AR(2) residuals of the regression of the aggregate ratio on its first two lags as suggested by Acharya and Pedersen (2005). The aggregate measure of illiquidity for the bond market (*ILB*) is constructed in a similar way but using data from TRACE.[10]

2.3 Other Aggregate (Control) Variables

In addition to aggregate illiquidity measures, we consider series of additional aggregate potential determinants of CDS spreads. Corporate CDS spreads might include a premium for bearing risk associated with the state of the economy. To the extent that macroeconomic conditions affect the risk preferences of participants in

[9] We use data from CRSP and only data on stock returns and trading volume from the NYSE.

[10] We employ the Amihud aggregate measure calculated by Monkerud, Nieto, and Rodriguez (2012). The actual procedure is described in their paper. It is the average aggregate illiquidity ratio using corporate bonds from the components of the S&P100 index. We thank Belén Nieto for kindly providing us this measure.

the CDS market, we would expect to find economic and statistically significant relationships between CDS spreads and aggregate variables. To capture the state of the economy or, even more importantly, to predict future real activity, we should employ state variables with proved predicting capacity of future output growth.

The term spread, measured as the difference between the interest rates on long and short maturity government debt, is probably the most common financial leading indicator of real activity. Among many others, Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Stock and Watson (2003), and Ang, Piazzesi, and Wei (2006) show the significant predictive content of the spread for production growth, including its capacity to forecast a recession indicator in probit regressions. Additionally, there is a growing body of literature exploring the transmission of credit conditions into the real economy. Among recent papers, Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009) show the forecasting power of the term structure of credit spreads for future output growth. These authors argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predicting capacity of credit spreads. We approximate the slope of the US term structure of interest rates by the difference between 10-year constant maturity Treasury bond yields and the 3-month constant maturity Treasury bill yields (TERM). Moreover, to capture the credit conditions, we use the difference between Moody's Aaa and Baa bond yield indices (DEF). These two measures, reflecting the unexpected changes in the term structure of interest rates and in default risk, have also been used by Acharya et al. (2010) as relevant time series determinants of the corporate bond yields, and by Gebhardt, Hvidkjaer, and Swaminathan (2005) in their cross-sectional analysis of corporate bond returns.

There has been considerable recent attention to financial uncertainty as a predictor of real activity. An increasingly popular measure of the risk premium potentially embedded in financial uncertainty is given by the variance risk premium (VRP) as discussed by Bollerslev, Tauchen, and Zhou (2009), Longstaff, Pan, Pedersen, and Singleton (2011) and Nieto, Novales, and Rubio (2011). It is well known that the difference between the realized volatility during a particular month and the risk neutral counterpart represented by VIX gives the (annualized) monthly volatility risk premium proxy. The realized variance is estimated as the (annualized) squared daily returns for a given month of the S&P500 index. The variance risk premium is reported to be negative on average.[11] It may be noted that the difference between the realized variance and (the square of) VIX can be understood as the payoff of a variance swap contract. The average negative payoff of the contract suggests that investors are willing to accept negative returns for purchasing realized variance. Equivalently, investors who are sellers of variance and are providing insurance to the market, require

[11] See Carr and Wu (2009)

substantial positive returns. This may be rational since the correlation between volatility shocks and market returns is known to be strongly negative and investors want protection against stock market crashes.

Finally, the aggregate risk preferences of market participants are proxy by the time-varying relative risk aversion (*RA*) measure under habit preferences based on the consumption surplus ratio of Campbell and Cochrane (1999). It is estimated as,

$$RA_t = \frac{\gamma}{S_t} \tag{5}$$

where S_t is the surplus consumption ratio given by $S_t = (C_t - X_t)/C_t$, C_t is the monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services, X_t is the level of habit approximated by an autoregressive process consistent with a low volatile enough interest rate, and γ is utility curvature.[12]

2.4 Descriptive Statistics of Aggregate Variables

Table 3 provides the summary statistics of the aggregate illiquidity measures and the macroeconomic control variables. In Panels A and B we further break down the summary statistics of the aggregate illiquidity measures for the CDS market given by the aggregate absolute bid-ask spread and aggregate gamma of CDS spreads and returns respectively by portfolio rating and maturity. From Panel A we observe that, for a given credit rating, the shorter maturities are always more illiquid than longer maturities. This is especially the case for the shortest maturity portfolios which are relatively highly illiquid contracts. The 5-year CDS contracts are the most liquid with the only exception of the high yield portfolios in which the 5-, 7-, and 10-year maturities have approximately the same illiquidity level. Therefore, the (average) slope of the term structure of bid-ask illiquidity for CDS spreads presents an asymmetric U-shaped pattern. At the same time, the standard deviation of portfolio illiquidity decreases almost everywhere as maturity increases. On the other hand, for a given maturity, portfolio illiquidity increases as the credit quality of the portfolio drops. This holds for portfolio CDS spreads for all maturities in terms of both mean and median, and it also holds for the standard deviation of illiquidity. Moreover, holding maturity constant, the increase in portfolio illiquidity is considerable when moving from the investment grade to the high-yield category of CDS portfolios. For

[12] We obtain nominal consumption expenditures on nondurable goods and services from the Table 2.8.5 of the National Institute of Pension Administrators (NIPA). Population data are from NIPA's Table 2.6 and the price deflator is computed using prices from NIPA's Table 2.8.4 with the year 2000 as its basis. All this information is used to construct monthly seasonally adjusted real per capita consumption expenditures on nondurable goods and services. The autoregressive parameter of the habit process is estimated using the price-dividend ratio obtained from the original series on Robert Shiller's website. The actual procedure to estimate the surplus consumption ratio follows the methodology described by Campbell and Cochrane (1999) with $\gamma = 2$. This utility curvature generates a stochastic discount factor with a mean value close to the inverse of the risk free rate during the sample period.

instance, the average of the most liquid 5-year bid-ask spread of AAA/A- and BBB+/BBB- portfolios are around 6 and 7 basis points, whereas the average 5-year bid-ask spread of BB+/B- and B+/D are around 17 and 43 basis points respectively.

[INSERT TABLE 3 ABOUT HERE]

Figure 3 depicts the time series of aggregate bid-ask spreads by maturity. We observe that the lower the maturity, the higher the illiquidity of the CDS contracts. This is particularly the case during stress periods, with the known exception of the 5-year contract which is overall the most liquid contract. As expected, the illiquidity of the CDS market increases substantially after the start of the financial crisis and it reaches its peak at the end of 2008 around the collapse of Lehman Brothers.

[INSERT FIGURE 3 ABOUT HERE]

In the case of the gamma measure of illiquidity, displayed in Panel B of Table 3, portfolio CDS bid-ask spreads increase across both maturity and credit quality almost everywhere. Although the increasing monotonic illiquidity relation throughout credit ratings is maintained for all maturities, the opposite result is observed with respect to maturity for a given credit quality. Figure 4 plots the time series pattern of the gamma measure of illiquidity.

[INSERT FIGURE 4 ABOUT HERE]

Panel C of Table 3 also reports descriptive statistics for aggregate illiquidity for alternative horizons without distinguishing across credit quality both for bid-ask spreads and the gamma measure, market-wide illiquidity of the stock and corporate bond markets, time-varying risk aversion, the variance risk premium, the slope of the term structure and default risk. As before, aggregate illiquidity measured by the absolute bid-ask spread shows that short-term maturity contracts are highly illiquid, the average variance risk premium is negative, and the slope and default state variables are, as expected, positive on average during our sample period. Figure 5 and 6 depict the time series of aggregate Amihud ratio and aggregate Amihud illiquidity, the AR(2) residuals, for the US stock and bond markets respectively. The behavior of these two series is very close over time. It suggests spillovers of market-wide illiquidity from the stock to the bond market and vice versa. Figures 7 display the aggregate time-varying risk aversion under habit preferences. Risk aversion tends to increase during stress periods but, of course, it is striking the enormous increase of risk aversion during the current economic and financial crisis. It reaches unknown levels of risk aversion which should strongly impact discount rates and financial prices. Figure 8 represents the annualized volatility risk premium. As expected, the volatility under the risk neutral measure tends to be higher than the volatility under the objective probability measure except in periods of great distress in which realized volatility is extremely high.

[INSERT FIGURE 5 and 6 ABOUT HERE]

Table 4 displays the correlation matrix among the aggregate illiquidity and other control variables. Panel A contains the correlations for the whole sample period from January 2004 to April 2011, whereas Panels B and C present the correlations for the expansion (January 2004 to June 2007) and recession (July 2007 to April 2011) sub-periods respectively. From Panel A we observe that there is a high level of correlation among bid-ask spreads of CDS contracts for different maturities. More specifically, all the pairwise correlation coefficients between any two series of bid-ask spreads with different maturities are higher than 90%. This already suggests that there might be a high commonality in bid-ask spreads of different maturities. The pattern of high correlation holds also for gamma illiquidity measures of CDS spreads. The correlation among aggregate bid-ask spreads and gamma illiquidity across different maturities is higher than 70%.

The aggregate illiquidity measure for the US equity market has a relatively high (above 0.30 and less than 0.65) correlation with the aggregate illiquidity measures of CDS spreads. However, despite the 0.37 correlation between *ILS* and *ILB*, the illiquidity measures for the fixed income market has a much lower, and even negative, correlation with the CDS market illiquidity. It should be recalled that *ILB* is calculated only with corporate bonds from companies of the S&P100 index. The association of macroeconomic variables is higher with aggregate bid-ask spreads than with the gamma measure of illiquidity. We also observe moderate and positive correlation coefficients between alternative aggregate illiquidity variables of the CDS market and both, the variance risk premium and changes in default risk. It is interesting to note the negative correlation between the variance risk premium and aggregate risk aversion. When risk aversion increases, the expected variance under the risk neutral measure becomes higher relative to realized variance generating a negative association between these two variables.

Looking now at Panels B and C of Table 4, it turns out that the correlation among illiquidity and macroeconomic variables increase from the expansion to recession sub-periods nearly in all pairwise scenarios. This is especially evident for the correlations among the aggregate illiquidity measures of the CDS market.

[INSERT TABLE 4 ABOUT HERE]

3 Effects of Market-Wide Illiquidity on CDS Spreads

3.1 Illiquidity Commonality

As already mentioned before, the results of Table 3 suggest that there is a high level of liquidity commonality among aggregate bid-ask spreads of CDS contracts of different maturities. To examine the degree of commonality of CDS illiquidity spreads in terms of the overall aggregate bid-ask spreads, we run the following ordinary least squares (OLS) autocorrelation-robust standard error regressions:

$$\Delta PILBASy_t = a + b\Delta ILBAS_t + \varepsilon_t \tag{6}$$

where $\Delta PILBASy_t$ is the change of the bid-ask spread of credit-quality-sorted portfolio p at month t with either 1-, 3-, 5-, 7-, or 10- year maturity, and $\Delta ILBAS_t$ is the maturity independent aggregate bid-ask spread of the CDS market. Before constructing the aggregate measure of bid-ask spread illiquidity of the market, individual bid-ask spreads of a CDS name are averaged across maturity. Table 5 contains the empirical results. It shows that there is a strong commonality across all portfolios and maturities. Most of the slope coefficients are positive and statistically significant. However, it is striking the strong illiquidity commonality, both in terms of regression coefficients and R-squared statistics, for high-yield underlings with ratings from BB+ to D. More importantly, this is especially the case for the higher default risk portfolio with ratings from B+ to D. Aggregate illiquidity seems to have an enormous impact on the CDS market segment of the lowest credit-quality-sorted portfolios.

[INSERT TABLE 5 ABOUT HERE]

3.2 Market-wide Illiquidity and CDS spreads

We next investigate the relationship between changes in CDS spreads and market-wide illiquidity. For a given maturity, and for each portfolio p of a particular credit quality, we run the following OLS autocorrelation-robust standard error regressions:

$$\begin{aligned}\Delta CDS_{pt} &= \beta_{p0} + \beta_{pilbas}\Delta ILBASy_t + \beta_{pils}ILS_t \\ &+ \beta_{pra}RA_t + \beta_{pvrp}VRP_t + \beta_{pterm}\Delta TERM_t + \beta_{pdef}\Delta DEF_t + e_{pt}\end{aligned} \tag{7}$$

where ΔCDS_{pt} is the change of the monthly CDS spread of portfolio p, $\Delta ILBASy_t$ is the change of the aggregate (equally weighted) absolute bid-ask spread for a given maturity, and the other variables have previously been defined.

Table 6 contains the regression results where each panel corresponds to a given horizon of 1-, 3-, 5-, 7-, and 10- year maturities. We show the empirical results for the full period, and also for two sub-periods that we relate to expansion and distress scenarios respectively. The key result of this section is the positive relationship between changes in portfolio CDS spreads and changes in the aggregate bid-ask spread measure of illiquidity of the CDS market. The regression coefficients, which we interpret as illiquidity CDS betas, are estimated with precision across credit ratings, maturities, and alternative sample periods. More specifically, nearly for all specifications of portfolio CDS maturity and rating groups, the illiquidity betas are positive and statistically significant for standard confidence levels. Moreover, as one would expect, the magnitude of the coefficients tends to be larger for high yield underlings. Therefore, low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. This is a robust and economically important result. It suggests that changes of CDS spreads are not only determined by changes in the credit quality of the underlying corporate bond. In other words, CDS spreads do not only reflect expected default and the associated default risk premium, but also expected market-wide illiquidity and the related illiquidity risk premium. A consequence of this result is that, at least for corporate CDS contracts, the well known one-factor intensity model for pricing CDS spreads of Pan and Singleton (2008) is likely to be badly specified.

In terms of sub-periods, for the 3-, 7-, and 10- year maturities, CDS spreads of low credit quality portfolios tend to have higher illiquidity betas during the distress period than during the expansion years. These high-yield distressed illiquidity betas are estimated with high precision. For the 1-, and 5- year maturities their sensitivities to illiquidity shocks seem to be equally relevant during both expansion and recession sub-periods. Overall, higher market-wide illiquidity tends to be accompanied by high CDS spreads both before and after June 2007 regardless of CDS maturity and credit rating.

The aggregate measure of Amihud illiquidity of the US equity market tends to be a significant factor mainly for AAA to A- rated CDS portfolios. The regression coefficients are always positive and they are estimated with precision. This is the case regardless of the portfolio maturity or the sample period of the analysis. Therefore, possible spillovers effects of market-wide illiquidity equity shocks seem to be relevant especially for highly rated underlings. However, it turns out that for all maturities, except for the shortest 1-year horizon, equity market-wide illiquidity seems to be also significant during the expansion sub-period. In other words, during non-recession moments of time equity illiquidity affects CDS spreads but this is not the case for distress periods where the aggregate illiquidity of the CDS market plays a more significant role.

The uncertainty embedded in financial assets, and proxy by the volatility risk premium, is also mainly related to AAA to A- CDS portfolios. The regression coefficients of these CDS portfolios are negatively and significantly related to VRP. Once again, as in the case of illiquidity spillover effects, it seems that equity volatility shocks only impact CDS spreads of highly rated underlings. However, there is an important difference with the previous result. Equity illiquidity spillovers tend to be relevant during the expansion sub-period, whereas equity volatility spillover shocks from the stock market to the CDS market of high credit quality portfolios are exclusively due to the recession sub-period. It is interesting to note the negative relationship between VRP and CDS spreads. It should be recalled that the VRP is estimated as the difference between the ex-post realized volatility and VIX. This is just the payoff of the future contract on realized variance. This means that when realized volatility is not as high as expected, traders on the CDS market interpret the lower observed volatility as good news for the economy, and CDS spreads become lower.

Time-varying risk aversion under habit preferences does not seem to be a consistently price factor in the CDS spread market. Most of the regression coefficients are estimated with very low precision, and the signs of the coefficients change from positive to negative depending upon the sub-period and maturities of the analysis. The only consistently priced CDS spread correspond to the B+ to D portfolio from January 2004 to June 2007. The coefficient is positive and significantly different from zero. As shown in Figure 7, increasing changes in RA start well before the beginning of the financial crisis. It may easily be the case that this pattern of increasing uncertainty is the source of the positive regression coefficient between CDS spreads of low credit quality underlings and time-varying risk aversion.

In general, inverted zero-coupon curves tend to anticipate recessions, while upward-sloping curves tend to forecast expansions. This suggests that increases in TERM should be negatively related to changes in CDS spreads. This state variable does not seem to be a consistently important factor in the CDS market. The regression coefficients tend to be negative but they are estimated with very low precision. The only exception is the behaviour of BBB+ to BBB- credit quality portfolios which show a relatively well estimated coefficient especially at long horizons. It may be that this segment is dominated by an industry particularly sensitive to interest rate risks.

Finally, changes in DEF are one of the key factors that consistently explain changes in CDS spreads. DEF reflects aggregate default risk and, therefore, we expect a positive sign for the regression coefficients. This is systematically the case, although they are not always significantly different from zero. It turns out that, when estimated with precision, the low credit quality portfolios tend to have a stronger positive relationship between default risk and CDS spreads than other better credit rating assets. However, the most consistently default risk priced portfolio corresponds to the best credit ranking underlings. The AAA to A- CDS portfolio always presents a positive and significant regression coefficient which becomes lower the longer the maturity of the contract. This is a relevant finding that reflects how high quality corporate bonds react to aggregate default risk of the US economy. Moreover, default risk is priced especially during the boom sub-period. There are very few significant regression coefficients during the stress sub-period. This indicates that default risk impacts the CDS market mainly when there is a potential change in expectations. During the recession sub-period DEF seems to affect only high quality CDS portfolios. The situation may be so deteriorated that all potential aggregate default risk is already discounted in CDS spreads.

Overall, our selected market-wide variables explain a higher percentage of the variability of the AAA to A- CDS portfolio than the variability of the rest of portfolios. This finding becomes stronger the longer the maturity of the CDS portfolio. On average, the R-squared statistics for this high quality portfolio is approximately 0.57 for the full period across all five maturities. The expansion sub-period presents an average R-squared statistics across portfolios and maturities of 0.52, whereas the average statistic during the recession sub-period is 0.43. However, this lower explanatory power is not due to the AAA to A- CDS portfolio. Indeed, the highest R-squared coefficient across all regressions is 0.65 which corresponds to the better rating portfolio and the 10- year maturity contract. The model seems to price reasonably well CDS spreads but it is also true that the model has a larger average explanatory power during expansions, and it seems to fit better the high quality contracts relative to other CDS spreads.[13]

To conclude, market-wide illiquidity in the CDS market, financial uncertainty represented by the volatility risk premium, and default risk are the aggregate variables that are systematically related to changes in CDS spreads. Additionally, spillover illiquidity effects from the equity market are consistently associated with the AAA to A- CDS portfolio.

[INSERT TABLE 6 ABOUT HERE]

[13] Alternative specifications with either levels or changes of RA and VRP, and with or without RA or TERM do not seem to affect the overall conclusions.

4 Flight-to-liquidity, flight-to-quality and CDS spreads

The result of the previous section show that, especially in distress macroeconomic scenarios, a negative market-wide illiquidity shock in the CDS market raises the sensitivity of CDS spreads to those shocks. This effect is stronger in junk underlings than in high quality corporate bonds. This result suggest that investors may substitute less liquid corporate bonds for highly liquid bonds which should consequently raise the CDS spread associated to those bad quality bonds. Therefore, we may have a flight-to- liquidity phenomenon reflected even in the CDS market and not only on the corporate bond market. At the same time, and for similar reasons, we may have a possible distinct flight-to-quality episode. The section investigates whether the CDS market reflect either a flight-to-liquidity or flight-to-quality or both.

We study how the difference between the CDS spread of the B+ to D and the spread of the AAA to A- portfolio is explained by default and illiquidity market-wide risks in expansion and in moments of financial distress. Hence, we first form an additional CDS portfolio as the difference of the spreads between out two extreme portfolios. Secondly, we perform OLS autocorrelation-robust standard error regressions of the form,

$$\begin{aligned}
\Delta CDS_{pt}^{LH} &= \beta_{p0} + \beta_{pilbas}\Delta ILBASy_t + \beta_{pils}ILS_t \\
&+ \beta_{pra}RA_t + \beta_{pvrp}VRP_t + \beta_{pterm}\Delta TERM_t + \beta_{pdef}\Delta DEF_t \\
&+ \beta_{pdilbas}\Delta ILBASy_t \times D_t + \beta_{pdils}ILS_t \times D_t \\
&+ \beta_{pdra}RA_t \times D_t + \beta_{pdvrp}VRP_t \times D_t + \beta_{pdterm}\Delta TERM_t \times D_t + \beta_{pddef}\Delta DEF_t \times D_t + e_{pt} \quad (8)
\end{aligned}$$

where ΔCDS_{pt}^{LH} is now the difference between the CDS spreads of the junk portfolio given by the B+ to D ratings (L) and the CDS portfolio spreads associated with the AAA to A- underlings (H), and is a dummy variable taking the value of 1 during the financial crisis (second sub-period) and 0 otherwise. For each maturity, we run these regressions with and without the illiquidity aggregate variables, both from the CDS and equity markets, to check the differences between the cross-product terms of the illiquidity variables and the recession dummy. If the sign of the regression coefficient associated with the cross-product is negative and significant, once we include market-wide illiquidity, we may conclude that that there is flight-to-liquidity during stress times in the CDS market. We then pursue the same procedure to analyze the potential flight-to-quality in this market. We first run regression (8) omitting the default variable, and then we add it to check the sign and significance of the cross-product coefficient.

Table 7 contains the results regarding flight-to-liquidity. Each column corresponds to a given maturity where we report the results first without liquidity variables and then adding these variables and the cross-product terms. The first column reports the results for the shortest horizon. Both ILS and market-wide illiquidity in the CDS market present positive and significant results. However, the regression coefficient of $\Delta ILBAS_{1y}$ is estimated with much more precision than the coefficient of ILS. Additionally, there is a significant and negative coefficient of the cross-product term $\Delta ILBAS_{1y} \times D_t$ which suggests a short-term flight to liquidity in this market given the inversion of the slope of the term structure of CDS spreads during the stress sub-period for the 1- year horizon. For the rest of maturities, our results do not seem to present incremental differences on the impact of market-wide illiquidity variables. The flight-to-liquidity finding is exclusively a short-term phenomenon. It is important to point out the very large increase experimented by the explanatory of the model when we include market-wide illiquidity variables. Although the highest R-squared statistic is obtained for the model with illiquidity variables during the crisis sub-period, it should be noted that the percentage increase of the R-squared once we incorporate the illiquidity variables is higher the longer the maturity of the CDS contract. These regression results therefore show the enormous importance of aggregate illiquidity shocks to explain the differential CDS spreads between bad quality CDS portfolios relative to highly rated portfolios. Overall, the spread differential significantly increase when there is an adverse shocks to market-wide illiquidity in the stock market independently of the maturity of the CDS contract. However, this effect is only significant for the aggregate illiquidity of the CDS market for maturities with 1- and 5- year contracts.

[INSERT TABLE 7 ABOUT HERE]

Table 8 shows the same results where we now omit the default risk variables rather than the illiquidity variables. It turns out that default risk seems to be much less important for explaining changes in the differential CDS spreads than illiquidity risk. The R-squared statistics are practically the same independently of adding default risk into the regression or not. Moreover, this result holds for all maturities. We do not find any significant evidence of flight-to-credit quality in the CDS market during the stress sub-period. We already discussed in Section 2 that we also consider an alternative measure of aggregate illiquidity on the CDS market given by the covariance between adjacent returns or the gamma measure of illiquidity. Moreover, we also employ an aggregate measure of illiquidity in the corporate bond market using the Amihud ratio for the corporate bonds of the components of the S&P100 index estimated with TRACE. The overall results with these alternative measures are the same as the empirical evidence reported in Tables 6, 7 and 8. Market-wide illiquidity is an important determinant of changes of corporate CDS spreads. The detailed evidence is contained in Appendices A, B, C and D for the bid-ask spread and ILB, the gamma illiquidity measure and ILS, the gamma illiquidity measure and ILB, and the flight-to-liquidity/flight-to-quality evidence respectively.

[INSERT TABLE 8 ABOUT HERE]

5 Conclusions

The recent financial crisis has raised some concerns about the liquidity of CDS contracts. At this point, it is generally accepted that CDS spreads cannot be understood as a pure measure of creditworthiness of a company. CDS spreads can be explained by factors related not only to the credit risk of a company, but also to liquidity related components. Although, there are several papers analyzing the relationship between CDS spreads and illiquidity proxies, there is no work that has focused on the effects of aggregate illiquidity from the CDS, equity, and corporate bond markets on CDS spreads.

In this paper we find a strong commonality in the illiquidity of CDS portfolios. This suggests that measures of market-wide illiquidity may explain changes on CDS spreads. Indeed, this turns out to be the case. There is a positive and significant relationship between changes in CDS spreads and changes in aggregate bid-ask spread for a given maturity of the CDS contract. Illiquidity CDS betas across credit quality portfolios and maturities are positive and statistically significant. Our evidence is a strong and robust to alternative market-wide measures of illiquidity from other markets, and other macroeconomic control measures. Moreover, as one would expect, the magnitude of the coefficients tends to be larger for high yield underlings. Therefore, low credit rating CDS spreads tend to be highly sensitive to aggregate illiquidity shocks relative to high credit quality CDS spreads. This is particularly the case during the recession sub-period. There is also evidence of flight-to-liquidity during stress periods, at least at short horizons.

Overall, our empirical evidence suggests that changes of CDS spreads are not only determined by changes in the credit quality of the underlying corporate bond. In other words, CDS spreads do not only reflect expected default and the associated default risk premium, but also expected market-wide illiquidity and the related illiquidity risk premium. A consequence of this result is that the well known one-factor intensity model of Pan and Singleton (2008) is likely to be badly specified when used for pricing corporate CDS contracts. In future research, we plan to extend the one-factor pricing intensity model by adding an illiquidity factor. The fact that illiquidity CDS betas are positive and significant suggests a high and economically relevant illiquidity risk premium in the CDS market.

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Table 1: CDS names by Sector and Rating

	AA	A	BBB	BB	B	CCC	Total
Basic Materials		1	7	6	2		16
Consumer Goods		1	13	12	1	6	42
Consumer Services	1	6	29	14	2	2	72
Financials	3	11	9	8	4	8	43
Health Care	1	6	2	3	2		14
Industrials	1	5	16	6	4		32
Oil & Gas		4	6	8	1		19
Technology		6	5	3	4		18
Telecommunications		7	2	4		1	14
Utilities		1	5	3	3	2	14
Total	6	48	94	67	5	19	284

This table shows the distribution of CDS names in our database by rating and ICB Industry category. The rating is the average of the Moody's and S&P ratings that are adjusted to the seniority of the instrument and are rounded not to include the plus and minus levels.

Table 2: Portfolio CDS Spreads

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	51.52	20.99	75.55	64.41	39.79	72.29	185.91	120.71	202.24	526.80	293.18	688.73
3y	59.61	36.91	67.28	84.45	60.79	69.05	249.60	189.71	175.46	642.15	445.50	597.18
5y	69.53	47.75	62.77	104.25	80.22	63.59	297.62	240.15	159.56	696.43	519.11	522.80
7y	73.61	56.10	56.59	111.91	92.00	56.23	308.67	255.50	141.38	690.32	545.11	463.65
10y	78.94	64.14	51.25	120.68	104.87	49.80	318.76	284.56	128.64	680.67	558.40	405.81

This table reports summary statistics for equally-weighted CDS spreads of credit-quality-sorted portfolios with different maturities. Before constructing portfolio CDS spreads, 1 and 99 percentiles of CDS spreads were removed from the *cross-sectional* distribution of CDS spreads for each month and maturity. The frequency of portfolio CDS spreads is monthly. The sample period spans from January 2004 to March 2011.

Table 3: Liquidity Proxies and Macro Variables

Panel A: Portfolio Bid-Ask Spreads

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	11.36	7.01	9.65	13.97	10.39	9.60	32.09	20.91	30.62	80.38	43.52	99.50
3y	8.43	6.18	5.27	10.48	8.37	4.89	23.33	18.85	16.49	55.42	31.66	68.77
5y	6.17	5.24	3.68	7.28	6.30	3.38	17.13	14.27	12.71	43.19	26.48	60.54
7y	7.07	5.91	3.19	8.74	7.78	2.77	18.66	16.06	11.65	43.17	26.50	61.18
10y	7.13	5.98	2.86	8.93	8.19	2.39	18.34	16.63	10.59	42.12	27.27	57.52

Panel B: Portfolio Gamma Illiquidity

	AAA to A-			BBB+ to BBB-			BB+ to BB-			B+ to D		
	mean	med	sd	mean	med	sd	mean	med	sd	mean	med	sd
1y	0.01	-0.00	0.11	0.02	-0.00	0.10	0.05	0.00	0.15	0.11	0.00	0.40
3y	0.21	0.00	0.83	0.25	0.00	0.77	0.60	0.03	1.30	1.14	0.04	2.59
5y	0.50	0.02	1.47	0.71	0.05	1.84	1.43	0.20	2.55	2.20	0.29	4.44
7y	0.73	0.02	2.21	1.02	0.06	2.65	1.97	0.18	3.74	3.15	0.38	5.40
10y	0.89	0.01	3.18	1.38	0.07	4.12	2.63	0.28	5.34	3.51	0.46	6.52

Panel C: Aggregate Iliquidity Proxies and Macro Variables

	mean	sd	min	5%	med	95%	max	Obs.
ILBAS1y	30.20	33.32	7.86	8.63	14.83	106.41	184.66	81
ILBAS3y	20.85	19.81	6.94	8.14	12.07	54.21	143.56	81
ILBAS5y	15.27	16.08	4.83	5.88	9.18	39.62	121.12	81
ILBAS7y	16.32	15.42	6.54	7.57	10.68	36.19	120.43	81
ILBAS10y	16.07	14.21	6.93	7.69	11.04	32.77	113.23	81
ILCOV1y	0.03	0.13	-0.03	-0.01	-0.00	0.13	1.05	87
ILCOV3y	0.38	1.00	-0.07	-0.03	0.01	1.78	7.60	87
ILCOV5y	0.93	2.02	-0.05	-0.00	0.07	4.89	14.26	87
ILCOV7y	1.33	2.85	-0.22	-0.16	0.07	6.55	19.85	87
ILCOV10y	1.71	4.13	-0.80	-0.38	0.07	6.33	31.33	87
ILS	-0.03	0.46	-1.92	-0.46	-0.04	0.49	2.52	84
ILB	0.00	0.09	-0.40	-0.11	-0.00	0.19	0.30	72
RA	51.13	38.11	23.74	24.26	28.58	130.24	139.00	84
VRP	-3.69	4.54	-12.65	-11.20	-3.60	3.41	16.65	88
TERM	1.82	1.37	-0.61	-0.32	2.14	3.52	3.78	88
DEF	1.18	0.62	0.60	0.71	0.94	2.93	3.43	88

This table reports the summary statistics for our illiquidity measures and macroeconomic variables. Panel A and B provide the summary statistics for Bid-ask spread and Gamma measure of illiquidity of the CDS market in terms of maturity and credit quality, respectively. Credit-quality-sorted bid-ask spreads and gamma measures are calculated in the same way as the portfolio CDS spreads. Panel C provides the summary statistics for the aggregate measures and macroeconomic variables. ILS and ILB are the aggregate measures of illiquidity for US stock and bond markets, respectively. RA is the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP is the variance risk premium, $TERM$ is the term spread of interest rate curve, and DEF is the default spread of Moody's. The frequency of all measures is monthly. The data for most of the measures are from January 2004 to April 2011.

Table 4: Correlation Matrix of Liquidity Proxies and Macro Variables

Panel A: Full Period (01/2004 - 04/2011)

	Δ ILBAS1y	Δ ILBAS3y	Δ ILBAS5y	Δ ILBAS7y	Δ ILBAS10y	Δ ILCOV1y	Δ ILCOV3y	Δ ILCOV5y	Δ ILCOV7y	Δ ILCOV10y	ILS	ILB	RA	VRP	Δ TERM	Δ DEF
Δ ILBAS1y	1															
Δ ILBAS3y	0.950	1														
Δ ILBAS5y	0.918	0.987	1													
Δ ILBAS7y	0.929	0.991	0.992	1												
Δ ILBAS10y	0.924	0.988	0.990	0.999	1											
Δ ILCOV1y	0.748	0.773	0.730	0.741	0.732	1										
Δ ILCOV3y	0.766	0.790	0.755	0.766	0.758	0.991	1									
Δ ILCOV5y	0.720	0.736	0.701	0.710	0.703	0.977	0.990	1								
Δ ILCOV7y	0.747	0.755	0.728	0.738	0.731	0.958	0.981	0.991	1							
Δ ILCOV10y	0.783	0.822	0.798	0.806	0.801	0.958	0.979	0.973	0.979	1						
ILS	0.654	0.534	0.512	0.522	0.513	0.384	0.398	0.388	0.421	0.352	1					
ILB	-0.0722	-0.0673	-0.0526	-0.0739	-0.0866	0.0378	0.0317	0.0434	0.0146	-0.0635	0.370	1				
RA	-0.145	-0.0851	-0.0619	-0.0610	-0.0565	-0.0369	-0.0499	-0.0552	-0.0572	-0.0439	-0.0958	-0.0601	1			
VRP	0.528	0.438	0.378	0.385	0.372	0.433	0.431	0.441	0.432	0.405	0.578	0.386	-0.411	1		
Δ TERM	0.179	0.172	0.225	0.224	0.229	-0.0498	0.00615	0.0149	0.0844	0.0852	0.183	-0.0845	0.174	0.00488	1	
Δ DEF	0.473	0.394	0.393	0.376	0.370	0.268	0.265	0.269	0.276	0.226	0.719	0.559	-0.250	0.651	0.0248	1

Panel B: Expansion Period (01/2004 - 06/2007)

	Δ ILBAS1y	Δ ILBAS3y	Δ ILBAS5y	Δ ILBAS7y	Δ ILBAS10y	Δ ILCOV1y	Δ ILCOV3y	Δ ILCOV5y	Δ ILCOV7y	Δ ILCOV10y	ILS	ILB	RA	VRP	Δ TERM	Δ DEF
Δ ILBAS1y	1															
Δ ILBAS3y	0.522	1														
Δ ILBAS5y	0.574	0.286	1													
Δ ILBAS7y	0.544	0.876	0.367	1												
Δ ILBAS10y	0.553	0.824	0.362	0.912	1											
Δ ILCOV1y	0.258	0.211	0.429	0.160	0.120	1										
Δ ILCOV3y	0.296	0.258	0.570	0.235	0.164	0.902	1									
Δ ILCOV5y	0.383	0.334	0.656	0.360	0.282	0.817	0.935	1								
Δ ILCOV7y	0.362	0.327	0.635	0.341	0.264	0.771	0.901	0.990	1							
Δ ILCOV10y	0.359	0.320	0.672	0.313	0.235	0.803	0.938	0.984	0.979	1						
ILS	0.442	0.495	0.431	0.494	0.430	0.162	0.227	0.342	0.338	0.321	1					
ILB	0.149	-0.111	0.234	-0.0862	-0.0608	0.182	0.102	0.111	0.0843	0.116	-0.0858	1				
RA	0.0692	-0.0764	0.0797	-0.0611	-0.0214	-0.0844	0.00487	-0.00446	0.00499	-0.0113	-0.0409	-0.0253	1			
VRP	0.276	0.452	0.320	0.352	0.344	0.0975	0.191	0.370	0.400	0.361	0.314	0.0265	0.0193	1		
Δ TERM	-0.0806	-0.266	-0.0382	-0.175	-0.159	0.0666	-0.0446	-0.0374	-0.0347	-0.0612	-0.0884	0.239	0.221	-0.212	1	
Δ DEF	0.227	0.176	0.279	0.244	0.300	0.0875	0.232	0.261	0.283	0.267	0.0918	-0.0239	-0.167	0.0648	-0.105	1

Panel C: Recession Period (06/2007 - 04/2011)

	Δ ILBAS1y	Δ ILBAS3y	Δ ILBAS5y	Δ ILBAS7y	Δ ILBAS10y	Δ ILCOV1y	Δ ILCOV3y	Δ ILCOV5y	Δ ILCOV7y	Δ ILCOV10y	ILS	ILB	RA	VRP	Δ TERM	Δ DEF
Δ ILBAS1y	1															
Δ ILBAS3y	0.951	1														
Δ ILBAS5y	0.919	0.989	1													
Δ ILBAS7y	0.929	0.991	0.993	1												
Δ ILBAS10y	0.925	0.989	0.992	0.999	1											
Δ ILCOV1y	0.749	0.774	0.730	0.742	0.733	1										
Δ ILCOV3y	0.767	0.792	0.756	0.767	0.759	0.992	1									
Δ ILCOV5y	0.720	0.737	0.702	0.711	0.704	0.977	0.990	1								
Δ ILCOV7y	0.748	0.756	0.728	0.739	0.732	0.959	0.982	0.991	1							
Δ ILCOV10y	0.784	0.823	0.799	0.807	0.802	0.959	0.979	0.973	0.979	1						
ILS	0.674	0.545	0.525	0.536	0.527	0.399	0.412	0.400	0.434	0.362	1					
ILB	-0.0793	-0.0705	-0.0605	-0.0776	-0.0911	0.0395	0.0329	0.0446	0.0146	-0.0675	0.399	1				
RA	-0.208	-0.125	-0.0971	-0.0896	-0.0833	-0.0478	-0.0661	-0.0740	-0.0762	-0.0577	-0.193	-0.211	1			
VRP	0.552	0.452	0.394	0.400	0.387	0.455	0.453	0.461	0.450	0.422	0.605	0.424	-0.573	1		
Δ TERM	0.220	0.223	0.278	0.284	0.290	-0.0620	0.00827	0.0192	0.107	0.109	0.230	-0.205	-0.0291	0.0563	1	
Δ DEF	0.480	0.400	0.398	0.381	0.373	0.272	0.269	0.273	0.279	0.228	0.753	0.596	-0.340	0.692	0.0423	1

This table reports the correlation matrix among aggregate illiquidity variables with different maturities and maco finance variables. The data are from January 2004 to March 2011.

Table 5: Portfolio Bid-ask spread versus Aggregate bid-ask spread illiquidity

	Dep Var: Δ PILBAS1y			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.02	0.03	−0.07	−0.44
	(0.05)	(0.09)	(−0.08)	(−0.29)
Δ ILBAS	0.18***	0.10	1.22***	4.90***
	(3.21)	(1.60)	(9.50)	(55.55)
N	80	80	80	80
adj. R^2	0.289	0.141	0.849	0.941

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dep Var: Δ PILBAS3y			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.04	0.06	0.00	−0.56
	(0.19)	(0.32)	(0.01)	(−0.51)
Δ ILBAS	0.08**	0.07**	0.82***	4.56***
	(2.31)	(2.14)	(12.53)	(23.48)
N	80	80	80	80
adj. R^2	0.169	0.210	0.897	0.972

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dep Var: Δ PILBAS5y			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.01	0.01	−0.13	−0.70
	(0.06)	(0.07)	(−0.37)	(−0.54)
Δ ILBAS	0.05*	0.04**	0.74***	4.07***
	(1.75)	(2.04)	(14.15)	(20.99)
N	80	80	80	80
adj. R^2	0.116	0.156	0.872	0.963

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dep Var: Δ PILBAS7y			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.05	0.05	0.00	−0.49
	(0.33)	(0.43)	(0.00)	(−0.33)
Δ ILBAS	0.04	0.05**	0.74***	4.04***
	(1.64)	(2.33)	(15.86)	(18.42)
N	80	80	80	80
adj. R^2	0.098	0.156	0.909	0.963

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dep Var: Δ PILBAS10y			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.06	0.08	0.01	−0.53
	(0.44)	(0.61)	(0.05)	(−0.36)
Δ ILBAS	0.04	0.04**	0.71***	3.79***
	(1.57)	(2.27)	(16.85)	(17.20)
N	80	80	80	80
adj. R^2	0.077	0.109	0.909	0.960

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports monthly regressions with changes in 1- , 3-, 5-, 7-, 10 - year portfolio Bid-ask spread (equally weighted) as a dependant variable (constructed in the same way as credit quality sorted CDS spreads). t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity. N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS$ denotes changes in aggregate CDS Bid-ask spread (aggregated by maturity). "Maturity-independent" bid-ask spread series for each CDS name are constructed by averaging monthly bid-ask spreads over all maturities. ILBAS is constructed by averaging the cross sectional "maturity-independent" bid-ask spreads for each month. Before the aggregation 1st and 99th percentiles of absolute bid-ask spreads (maturity-independent) were dropped from the cross sectional distribution of absolute bid-ask spreads for each month.

Table 6: Portfolio CDS Spreads, Aggregate CDS Bid-ask spread and Stock Illiquidity.

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

Panel A: Maturity 1 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−2.69	4.42	2.84	12.27	−4.10	−14.56	−60.98*	−87.49	6.02	19.09**	10.91	51.11
	(−0.86)	(1.47)	(0.45)	(0.69)	(−1.32)	(−1.51)	(−2.03)	(−1.01)	(0.88)	(2.22)	(0.41)	(0.59)
Δ ILBAS1y	0.58***	0.50**	2.20***	12.87***	0.79***	2.17***	9.81***	30.52***	0.62***	0.52**	2.26**	13.35***
	(5.41)	(2.08)	(2.77)	(4.45)	(4.39)	(3.95)	(4.64)	(5.65)	(3.90)	(2.27)	(2.70)	(4.21)
ILS	22.07***	2.57	−21.07	−86.78	2.05***	4.81	13.05	75.28**	24.40**	5.87	−28.21	−122.01
	(2.70)	(0.19)	(−0.62)	(−0.96)	(3.03)	(1.58)	(1.09)	(2.45)	(2.15)	(0.37)	(−0.62)	(−1.06)
RA	−0.16	−0.04	0.10	−0.15	0.15	0.54	2.30**	3.55	−0.31*	−0.20**	0.02	−0.65
	(−1.66)	(−0.73)	(0.70)	(−0.25)	(1.24)	(1.47)	(2.07)	(1.07)	(−1.92)	(−2.15)	(0.08)	(−0.64)
VRP	−3.21**	0.75	2.81	3.65	−0.04	−0.24	−0.46	1.34	−4.30**	0.53	2.96	1.64
	(−2.15)	(0.85)	(1.06)	(0.42)	(−0.59)	(−1.29)	(−0.54)	(0.67)	(−2.12)	(0.58)	(0.90)	(0.15)
Δ TERM	3.12	−14.65	−11.67	2.94	0.07	−0.95	−4.47	−3.87	0.71	−27.58*	−18.20	−3.18
	(0.37)	(−1.45)	(−0.69)	(0.04)	(0.08)	(−0.68)	(−0.61)	(−0.17)	(0.06)	(−1.98)	(−0.56)	(−0.03)
Δ DEF	78.04**	2.94	139.58**	170.72*	8.20***	21.41**	70.82***	54.78	86.05**	−5.73	146.59*	226.66**
	(2.37)	(0.12)	(2.32)	(1.82)	(3.24)	(2.42)	(2.74)	(0.67)	(2.06)	(−0.19)	(1.96)	(2.22)
N	80	80	80	80	41	41	41	41	39	39	39	39
adj. R^2	0.452	0.249	0.526	0.482	0.612	0.495	0.488	0.612	0.440	0.258	0.496	0.442

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Maturity 3 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.77	3.16	0.81	23.47	−8.78*	−20.03	−129.13**	−169.40	7.43	17.60**	18.63	79.44
	(−0.72)	(1.11)	(0.15)	(1.34)	(−1.73)	(−1.31)	(−2.24)	(−1.16)	(1.37)	(2.07)	(0.95)	(1.08)
Δ ILBAS3y	0.50***	0.43*	2.64***	9.49***	0.40**	0.65	4.39**	1.08	0.53***	0.48**	2.74***	9.85***
	(4.22)	(1.88)	(4.50)	(3.57)	(2.11)	(1.35)	(2.18)	(0.18)	(3.95)	(2.33)	(4.60)	(3.64)
ILS	24.22***	9.08	12.06	8.63	4.37***	10.60***	31.58**	139.26***	27.67***	12.56	12.60	−0.04
	(4.63)	(0.75)	(0.53)	(0.13)	(4.23)	(2.85)	(2.29)	(5.11)	(4.08)	(0.94)	(0.41)	(−0.00)
RA	−0.13*	−0.04	−0.04	−0.23	0.34*	0.76	5.07**	7.28	−0.28**	−0.21**	−0.26	−0.92
	(−1.93)	(−0.74)	(−0.37)	(−0.44)	(1.69)	(1.34)	(2.26)	(1.32)	(−2.50)	(−2.05)	(−1.16)	(−1.18)
VRP	−2.68***	0.24	−0.36	3.96	−0.04	−0.18	−0.36	4.60	−3.61***	−0.10	−1.04	1.94
	(−2.65)	(0.26)	(−0.21)	(0.59)	(−0.40)	(−0.58)	(−0.35)	(1.49)	(−2.75)	(−0.10)	(−0.47)	(0.25)
Δ TERM	1.26	−14.40	−16.77	−0.13	0.08	−0.51	−1.16	4.42	−2.63	−27.32**	−31.00	−28.62
	(0.19)	(−1.50)	(−0.96)	(−0.00)	(0.09)	(−0.24)	(−0.15)	(0.16)	(−0.30)	(−2.17)	(−1.06)	(−0.32)
Δ DEF	64.06***	18.75	123.78**	148.18	17.04***	41.89***	160.50***	232.39**	67.90**	10.66	122.39*	159.59
	(3.22)	(0.81)	(2.36)	(1.31)	(5.47)	(4.38)	(3.96)	(2.69)	(2.69)	(0.39)	(1.98)	(1.21)
N	80	80	80	80	41	41	41	41	39	39	39	39
adj. R^2	0.562	0.276	0.576	0.401	0.560	0.339	0.441	0.438	0.570	0.283	0.556	0.354

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Maturity 5 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.75	2.12	2.42	21.81	−9.01	−13.05	-110.91^{**}	−64.05	8.06	16.62^{*}	16.74	88.70
	(−0.79)	(0.77)	(0.38)	(1.44)	(−1.25)	(−0.71)	(−2.32)	(−0.48)	(1.61)	(2.02)	(0.84)	(1.36)
Δ ILBAS5y	0.54^{***}	0.50^{*}	2.42^{***}	9.73^{***}	0.66^{**}	2.25^{**}	10.91^{***}	19.08^{***}	0.58^{***}	0.59^{**}	2.52^{***}	10.20^{***}
	(3.42)	(1.97)	(3.82)	(3.22)	(2.69)	(2.14)	(4.31)	(3.55)	(3.45)	(2.48)	(3.81)	(3.35)
ILS	24.04^{***}	10.20	23.88	15.12	6.42^{***}	10.32^{**}	31.93^{**}	85.37^{*}	27.57^{***}	13.61	25.32	12.63
	(5.46)	(0.90)	(1.24)	(0.23)	(3.69)	(2.35)	(2.08)	(1.93)	(4.97)	(1.09)	(0.95)	(0.15)
RA	-0.12^{**}	−0.04	−0.01	−0.30	0.36	0.49	4.40^{**}	3.03	-0.27^{***}	-0.21^{**}	−0.19	−1.14
	(−2.00)	(−0.72)	(−0.14)	(−0.65)	(1.25)	(0.69)	(2.41)	(0.57)	(−2.78)	(−2.12)	(−0.70)	(−1.53)
VRP	-2.53^{***}	−0.13	−0.01	1.52	−0.01	−0.27	−0.56	3.20	-3.42^{***}	−0.53	−0.43	−1.35
	(−2.96)	(−0.15)	(−0.00)	(0.27)	(−0.08)	(−0.76)	(−0.48)	(1.07)	(−3.15)	(−0.53)	(−0.14)	(−0.20)
Δ TERM	−1.79	-16.99^{*}	−19.67	−34.36	−0.73	−1.58	−1.81	0.31	−6.79	-30.55^{**}	−34.34	−76.84
	(−0.30)	(−1.88)	(−0.95)	(−0.69)	(−0.75)	(−0.68)	(−0.20)	(0.01)	(−0.85)	(−2.64)	(−1.04)	(−1.03)
Δ DEF	58.35^{***}	23.04	89.38	125.15	23.44^{***}	49.61^{***}	139.10^{***}	106.11	60.90^{***}	14.80	83.00	133.45
	(3.80)	(1.03)	(1.52)	(1.19)	(4.42)	(3.72)	(3.39)	(1.26)	(3.11)	(0.57)	(1.18)	(1.10)
N	80	80	80	80	41	41	41	41	39	39	39	39
adj. R^2	0.603	0.300	0.501	0.338	0.629	0.436	0.571	0.486	0.619	0.315	0.473	0.289

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel D: Maturity 7 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.79	1.31	0.76	16.71	−10.64	−20.15	−165.06**	−141.05	7.32	14.15*	13.01	80.39
	(−0.88)	(0.50)	(0.12)	(1.20)	(−1.22)	(−1.42)	(−2.28)	(−1.31)	(1.61)	(1.78)	(0.62)	(1.31)
Δ ILBAS7y	0.51***	0.47**	2.25***	9.45***	1.15**	3.43**	7.94	18.72*	0.55***	0.55**	2.37***	10.03***
	(4.10)	(2.13)	(4.00)	(3.17)	(2.61)	(2.48)	(1.36)	(1.78)	(3.93)	(2.67)	(3.89)	(3.28)
ILS	22.01***	10.75	18.52	15.00	5.60***	8.43**	30.52*	102.90***	25.20***	13.84	19.50	9.20
	(5.03)	(1.01)	(0.92)	(0.23)	(3.27)	(2.32)	(1.75)	(3.52)	(4.40)	(1.16)	(0.70)	(0.11)
RA	−0.11**	−0.04	−0.02	−0.30	0.42	0.77	6.65**	6.26	−0.25***	−0.19*	−0.18	−1.14
	(−2.06)	(−0.72)	(−0.19)	(−0.73)	(1.21)	(1.44)	(2.33)	(1.46)	(−2.96)	(−1.97)	(−0.64)	(−1.60)
VRP	−2.37***	−0.36	−0.45	0.25	−0.07	−0.37	0.42	4.19	−3.20***	−0.74	−1.06	−2.97
	(−3.08)	(−0.41)	(−0.22)	(0.05)	(−0.63)	(−1.38)	(0.40)	(1.32)	(−3.29)	(−0.74)	(−0.36)	(−0.47)
Δ TERM	−2.44	−17.40**	−24.09	−35.27	−0.17	−0.33	−7.28	19.48	−7.49	−30.23**	−35.94	−80.85
	(−0.44)	(−2.04)	(−1.32)	(−0.74)	(−0.20)	(−0.15)	(−0.74)	(1.46)	(−1.00)	(−2.73)	(−1.19)	(−1.12)
Δ DEF	54.33***	26.12	96.88*	121.88	25.20***	53.74***	198.42***	144.29	56.54***	18.87	92.95	138.56
	(4.07)	(1.21)	(1.71)	(1.45)	(5.13)	(5.09)	(4.13)	(1.42)	(3.28)	(0.75)	(1.38)	(1.43)
N	80	80	80	80	41	41	41	41	39	39	39	39
adj. R^2	0.608	0.315	0.470	0.336	0.623	0.525	0.453	0.573	0.625	0.326	0.446	0.290

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel E: Maturity 10 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.78	0.65	−0.08	17.13	−10.29	−19.62	−159.86**	−203.47	6.61	12.27	10.74	63.44
	(−0.97)	(0.26)	(−0.02)	(1.31)	(−0.91)	(−1.31)	(−2.25)	(−1.33)	(1.57)	(1.64)	(0.54)	(1.20)
Δ ILBAS10y	0.54***	0.54**	1.39**	9.59***	1.18***	3.36***	11.51***	12.96	0.58***	0.62***	1.52**	10.01***
	(4.49)	(2.37)	(2.17)	(3.57)	(2.98)	(3.10)	(3.88)	(1.48)	(4.30)	(2.86)	(2.29)	(3.65)
ILS	22.56***	11.29	11.12	36.93	6.58***	9.16**	27.12**	119.09***	25.82***	14.54	10.09	30.93
	(5.47)	(1.12)	(0.53)	(0.71)	(3.97)	(2.53)	(2.21)	(3.80)	(4.91)	(1.30)	(0.36)	(0.45)
RA	−0.10**	−0.04	−0.01	−0.26	0.41	0.76	6.47**	8.88	−0.23***	−0.18*	−0.16	−0.89
	(−2.11)	(−0.76)	(−0.06)	(−0.75)	(0.91)	(1.33)	(2.31)	(1.47)	(−3.07)	(−1.96)	(−0.61)	(−1.52)
VRP	−2.26***	−0.56	−0.48	0.91	−0.06	−0.40	0.45	5.82	−3.03***	−0.92	−1.17	−1.85
	(−3.31)	(−0.69)	(−0.27)	(0.24)	(−0.42)	(−1.43)	(0.41)	(1.66)	(−3.55)	(−0.97)	(−0.46)	(−0.38)
Δ TERM	−3.40	−18.66**	−30.48*	−30.22	−0.46	−0.33	−7.06	−16.72	−8.39	−31.37***	−43.02	−52.48
	(−0.69)	(−2.37)	(−1.81)	(−0.72)	(−0.57)	(−0.14)	(−0.78)	(−0.48)	(−1.26)	(−3.04)	(−1.50)	(−0.88)
Δ DEF	46.79***	26.61	122.63**	57.07	23.31***	55.25***	157.90***	204.75*	48.29***	19.21	124.98**	73.66
	(4.08)	(1.27)	(2.50)	(0.70)	(4.22)	(4.82)	(4.06)	(1.82)	(3.25)	(0.80)	(2.11)	(0.81)
N	80	80	80	80	41	41	41	41	39	39	39	39
adj. R^2	0.630	0.348	0.426	0.410	0.612	0.534	0.512	0.479	0.649	0.363	0.409	0.369

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Extreme Portfolio CDS Spreads, CDS Bid-Ask Illiquidity and Amihud Stock Illiquidity.

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependant variable. Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	33.97	44.04	46.44	70.08	47.61	79.52	37.41	71.36	19.75	54.73
	(0.55)	(0.54)	(0.94)	(1.01)	(1.07)	(1.30)	(0.86)	(1.24)	(0.49)	(1.10)
RA	−0.85	−1.60	−1.00	−2.08	−0.97	−2.61	−0.36	−2.06	0.45	−1.24
	(−0.36)	(−0.50)	(−0.51)	(−0.76)	(−0.55)	(−1.08)	(−0.21)	(−0.90)	(0.28)	(−0.63)
RA×D_t	1.61	1.27	1.22	1.47	0.85	1.75	0.31	1.19	−0.27	0.60
	(0.73)	(0.48)	(0.71)	(0.64)	(0.57)	(0.90)	(0.22)	(0.66)	(−0.21)	(0.38)
VRP	7.16**	1.72	9.02***	5.42*	8.32**	3.54	9.68***	4.90	11.11***	6.60*
	(2.13)	(0.96)	(2.99)	(1.94)	(2.60)	(1.25)	(3.03)	(1.58)	(3.06)	(1.89)
VRP×D_t	16.48	4.23	7.07	0.15	1.07	−1.46	−1.35	−4.65	−2.13	−5.38
	(0.89)	(0.41)	(0.51)	(0.02)	(0.09)	(−0.21)	(−0.12)	(−0.68)	(−0.21)	(−0.90)
Δ TERM	−0.47	1.21	10.34	13.36	7.90	6.30	19.79	27.76*	−11.95	−6.12
	(−0.02)	(0.05)	(0.44)	(0.48)	(0.39)	(0.26)	(1.12)	(1.93)	(−0.37)	(−0.16)
Δ TERM×D_t	80.76	−4.71	40.58	−38.61	19.69	−75.91	5.43	−100.43	69.16	−37.13
	(0.54)	(−0.04)	(0.36)	(−0.42)	(0.20)	(−1.02)	(0.06)	(−1.44)	(0.68)	(−0.55)
Δ DEF	153.50	29.60	225.60**	190.14*	174.04	63.83	182.80	96.82	236.75**	151.39
	(1.35)	(0.37)	(2.16)	(1.95)	(1.62)	(0.77)	(1.59)	(1.01)	(2.02)	(1.28)
Δ DEF×D_t	17.54	111.50	−56.81	−97.57	15.54	9.24	−8.88	−14.03	−96.65	−125.08
	(0.08)	(0.90)	(−0.30)	(−0.60)	(0.09)	(0.06)	(−0.05)	(−0.10)	(−0.59)	(−0.84)
ILS		70.44**		133.68***		76.10*		95.76***		109.35***
		(2.47)		(4.64)		(1.84)		(3.24)		(3.64)
ILS×D_t		−217.03*		−161.68*		−91.19		−111.99		−104.52
		(−1.88)		(−1.76)		(−0.98)		(−1.29)		(−1.45)
Δ ILBAS1y		30.55***								
		(6.10)								
Δ ILBAS1y×D_t		−17.82***								
		(−2.99)								
Δ ILBAS3y				0.30						
				(0.05)						
Δ ILBAS3y×D_t				9.01						
				(1.36)						
Δ ILBAS5y						19.28***				
						(3.35)				
Δ ILBAS5y×D_t						−9.67				
						(−1.49)				
Δ ILBAS7y								17.36		
								(1.64)		
Δ ILBAS7y×D_t								−7.89		
								(−0.72)		
Δ ILBAS10y										12.24
										(1.42)
Δ ILBAS10y×D_t										−2.81
										(−0.31)
N	83	80	83	80	83	80	83	80	83	80
adj. R^2	0.109	0.428	0.103	0.323	0.043	0.252	0.026	0.260	0.047	0.334

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

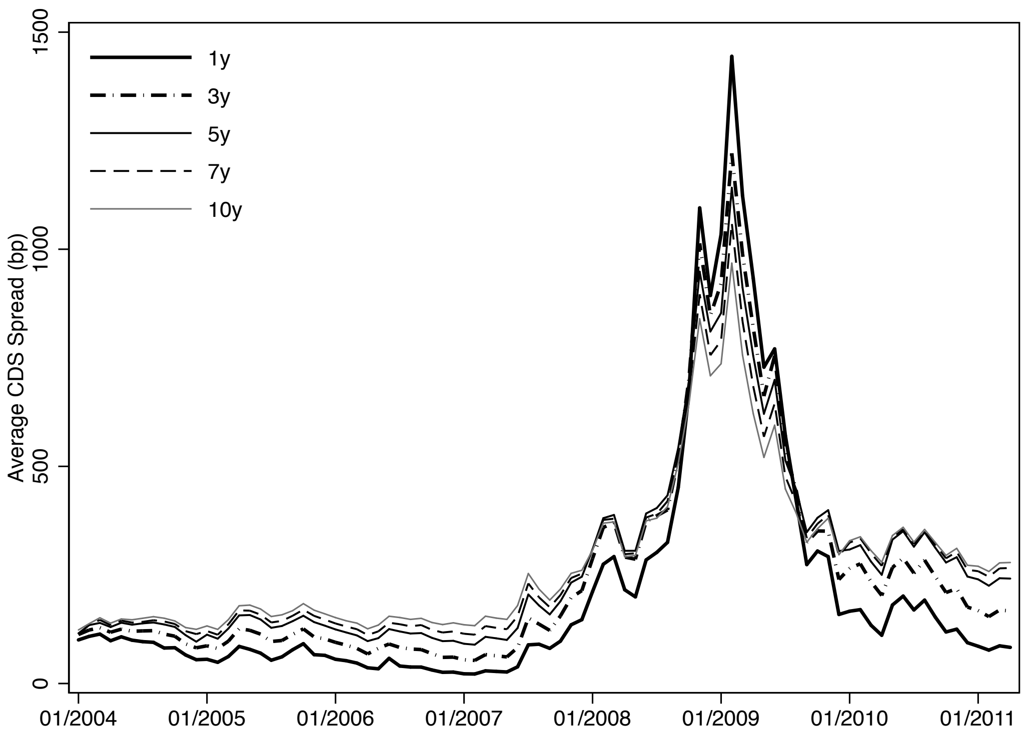
Table 8: Extreme Portfolio CDS Spreads, CDS Bid-ask Spread Illiquidity and Amihud Stock Illiquidity (**Without DEF**).

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS1y$ denotes changes in aggregate CDS Bid-ask spread (in annual basis points). $\Delta ILCOV1y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with 1 year maturity. ILS denotes the AR(2) residual of stationarized aggregate Amihud measure for the US stock market. ILB is the AR(2) residual of the aggregate Amihud measure for the US corporate bond market. RA denotes the risk aversion in levels for the gamma parameter equal to 2. VRP denotes the level of variance risk premium, which is calculated as the difference between the monthly realized volatility of the S& P500 index return (annualized) and the VIX index for the corresponding month. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	54.85	44.04	77.38	70.08	85.28	79.52	77.77	71.36	56.97	54.73
	(0.71)	(0.54)	(1.21)	(1.01)	(1.49)	(1.30)	(1.44)	(1.24)	(1.26)	(1.10)
Δ ILBAS1y	31.02***	30.55***								
	(6.42)	(6.10)								
Δ ILBAS1y×D_t	−18.43***	−17.82***								
	(−3.18)	(−2.99)								
Δ ILBAS3y			1.64	0.30						
			(0.26)	(0.05)						
Δ ILBAS3y×D_t			7.63	9.01						
			(1.11)	(1.36)						
Δ ILBAS5y					20.45***	19.28***				
					(3.75)	(3.35)				
Δ ILBAS5y×D_t					−10.82*	−9.67				
					(−1.74)	(−1.49)				
Δ ILBAS7y							18.95**	17.36		
							(2.02)	(1.64)		
Δ ILBAS7y×D_t							−9.50	−7.89		
							(−0.97)	(−0.72)		
Δ ILBAS10y									15.23**	12.24
									(2.12)	(1.42)
Δ ILBAS10y×D_t									−5.81	−2.81
									(−0.76)	(−0.31)
ILS	70.10**	70.44**	134.35***	133.68***	75.31*	76.10*	94.77***	95.76***	107.62***	109.35***
	(2.52)	(2.47)	(4.58)	(4.64)	(1.87)	(1.84)	(3.21)	(3.24)	(3.82)	(3.64)
ILS×D_t	−178.91	−217.03*	−138.79	−161.68*	−72.35	−91.19	−90.07	−111.99	−96.16	−104.52
	(−1.65)	(−1.88)	(−1.58)	(−1.76)	(−0.83)	(−0.98)	(−1.09)	(−1.29)	(−1.38)	(−1.45)
RA	−2.02	−1.60	−2.38	−2.08	−2.85	−2.61	−2.32	−2.06	−1.36	−1.24
	(−0.66)	(−0.50)	(−0.95)	(−0.76)	(−1.26)	(−1.08)	(−1.09)	(−0.90)	(−0.75)	(−0.63)
RA×D_t	1.67	1.27	1.75	1.47	1.97	1.75	1.43	1.19	0.71	0.60
	(0.66)	(0.48)	(0.83)	(0.64)	(1.07)	(0.90)	(0.83)	(0.66)	(0.49)	(0.38)
VRP	1.73	1.72	5.25**	5.42*	3.46	3.54	4.81	4.90	6.37*	6.60*
	(0.99)	(0.96)	(2.12)	(1.94)	(1.29)	(1.25)	(1.65)	(1.58)	(1.97)	(1.89)
VRP×D_t	6.26	4.23	1.60	0.15	−0.40	−1.46	−3.43	−4.65	−4.80	−5.38
	(0.60)	(0.41)	(0.20)	(0.02)	(−0.05)	(−0.21)	(−0.48)	(−0.68)	(−0.78)	(−0.90)
Δ TERM	1.07	1.21	10.83	13.36	5.02	6.30	26.52*	27.76*	−8.33	−6.12
	(0.05)	(0.05)	(0.34)	(0.48)	(0.20)	(0.26)	(1.72)	(1.93)	(−0.21)	(−0.16)
Δ TERM×D_t	−19.85	−4.71	−46.39	−38.61	−83.07	−75.91	−108.39	−100.43	−37.93	−37.13
	(−0.18)	(−0.04)	(−0.49)	(−0.42)	(−1.11)	(−1.02)	(−1.56)	(−1.44)	(−0.53)	(−0.55)
Δ DEF		29.60		190.14*		63.83		96.82		151.39
		(0.37)		(1.95)		(0.77)		(1.01)		(1.28)
Δ DEF×D_t		111.50		−97.57		9.24		−14.03		−125.08
		(0.90)		(−0.60)		(0.06)		(−0.10)		(−0.84)
N	80	80	80	80	80	80	80	80	80	80
adj. R^2	0.440	0.428	0.339	0.323	0.271	0.252	0.278	0.260	0.352	0.334

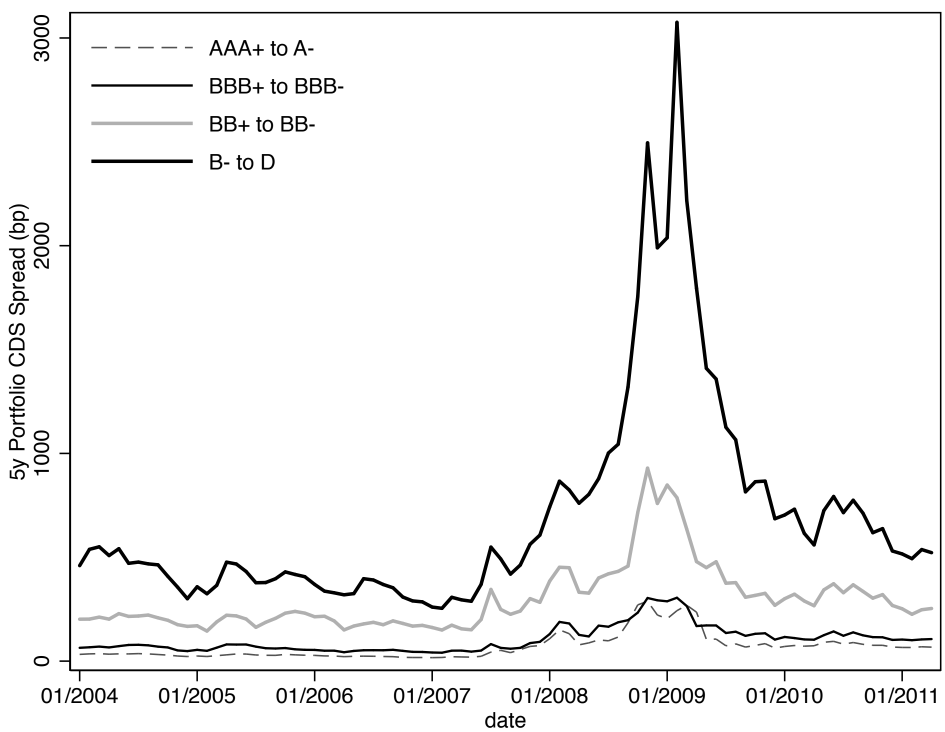
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Time series of sample mean CDS spreads.



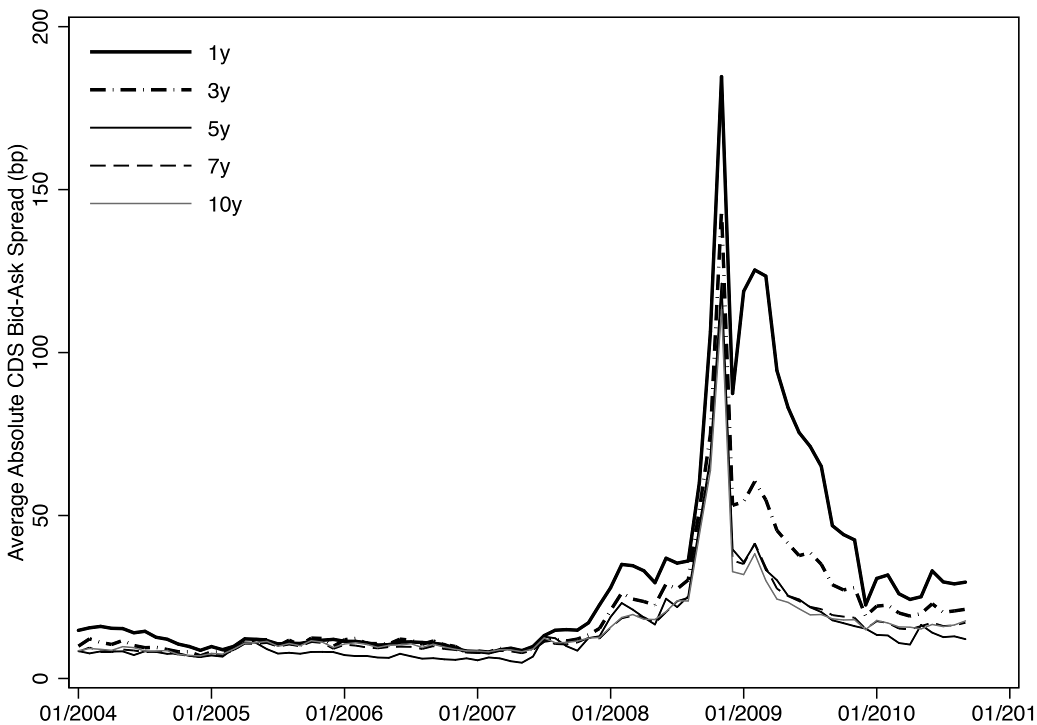
This graphs plots the monthly time series of CDS spreads by maturity. The time series of monthly CDS spreads for each maturity is constructed by taking the cross-sectional average of CDS spreads for each month and maturity. The time period of our sample spans from January 2004 to April 2011.

Figure 2: Time series of CDS spreads of credit quality sorted portfolios (equally weighted).



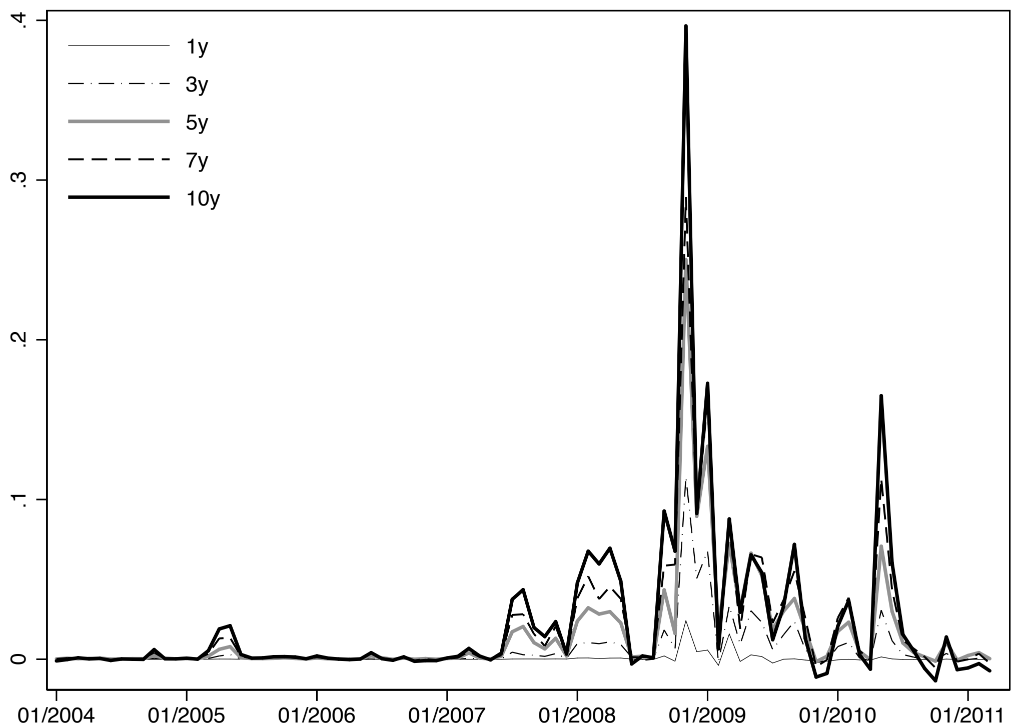
This graphs depicts the time series of CDS spreads of credit quality sorted portfolios. The 1st and 99th percentiles of CDS spreads were removed from the cross-sectional distribution of CDS spreads for each month before the calculation of the equally weighted portfolio CDS spreads. The time period of our sample spans from January 2004 to April 2011.

Figure 3: Time series of aggregate absolute CDS Bid-Ask Spread



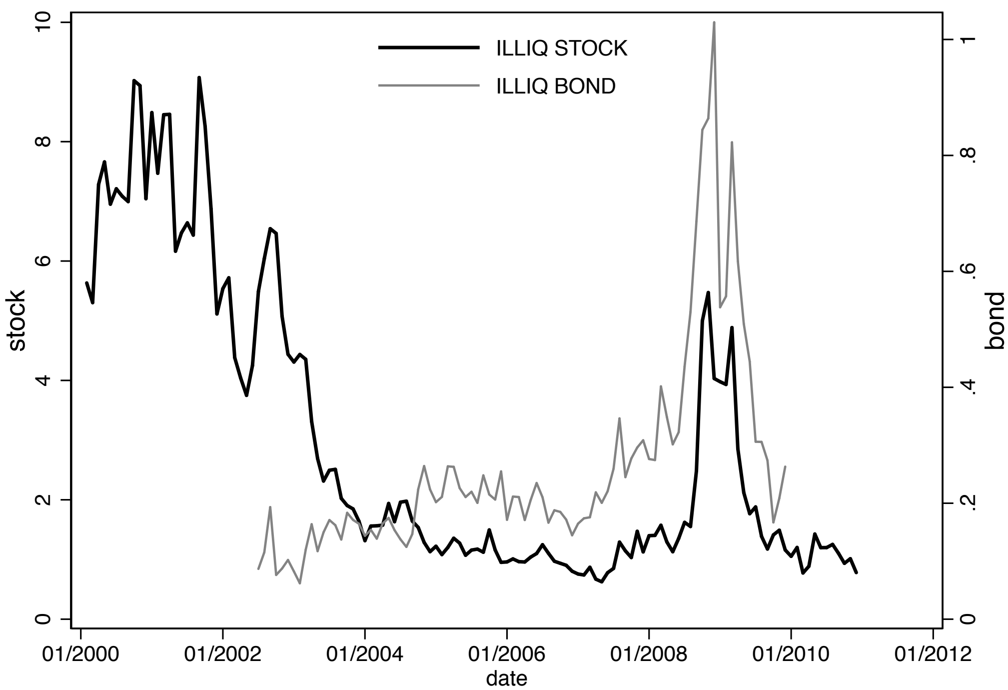
This graphs depicts the time series of aggregate Bid-ask spreads by maturity. The time series of aggregate Bid-ask spreads are obtained by taking the cross-sectional average of individual bid-ask spreads of CDS names in our database for each month and maturity. Before the aggregation the 1st and 99th percentiles of individual bid-ask spreads were removed from their cross sectional distribution for each month and maturity. The time period of our sample spans from January 2004 to September 2010.

Figure 4: Time series of aggregate measure of Gamma Illiquidity for CDS spreads



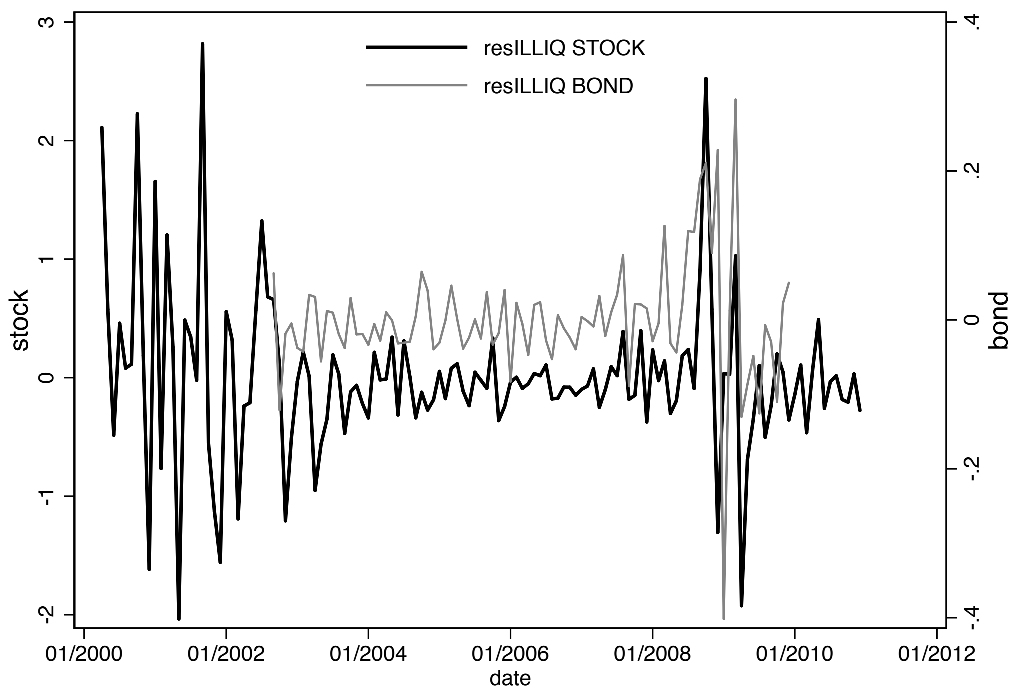
This graphs depicts the time series of aggregate measure of gamma illiquidity for CDS spreads. The aggregation is done by taking the cross sectional mean of individual gamma measures of illiquidity of all CDS name for a given month and maturity. Before calculating gamma measure of illiquidity for each CDS name and maturity, 5th and 95th percentiles of CDS returns were removed from the cross-sectional distribution of CDS returns for each month and maturity.

Figure 5: Time series of aggregate measure of Amihud ratio



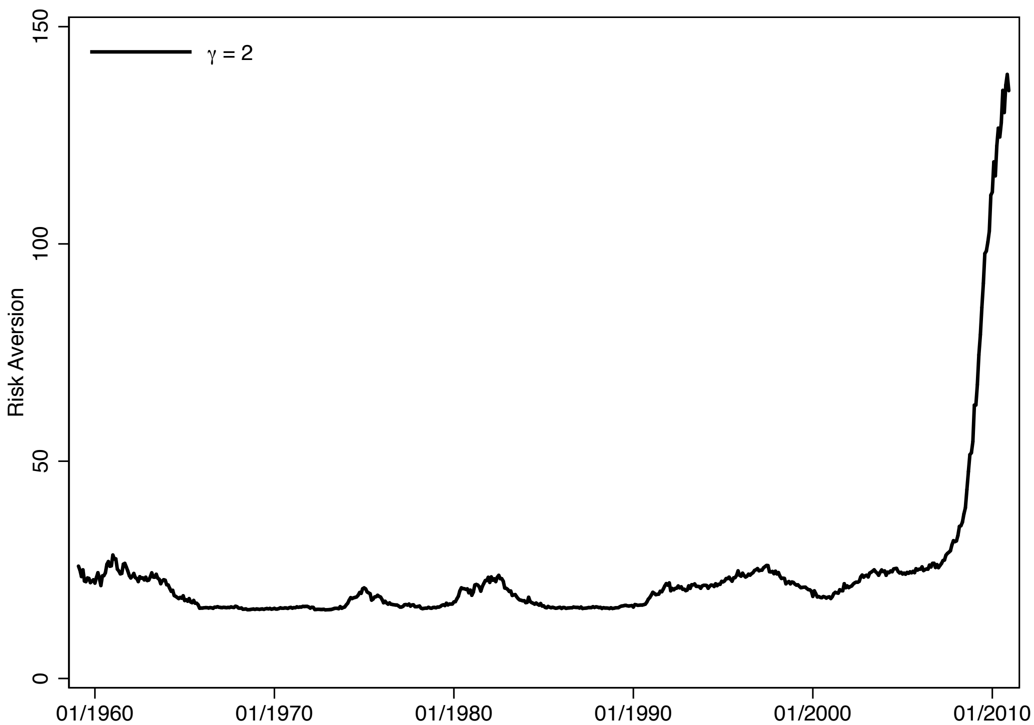
This graphs depicts the time series of the aggregate ratio of Amihud. The aggregation is done by taking the cross sectional mean of individual Amihud ratios for each month. When calculating the individual Amihud ratio for a month of a given stock, the stock returns that fall outside the 1st and 99th percentile of the cross-sectional distribution of stock return per trading volume were removed. The time period of the aggregate Amihud ratio goes from January 2000 to December 2011.

Figure 6: Time series of aggregate measure of Amihud illiquidity (AR(2) residuals)



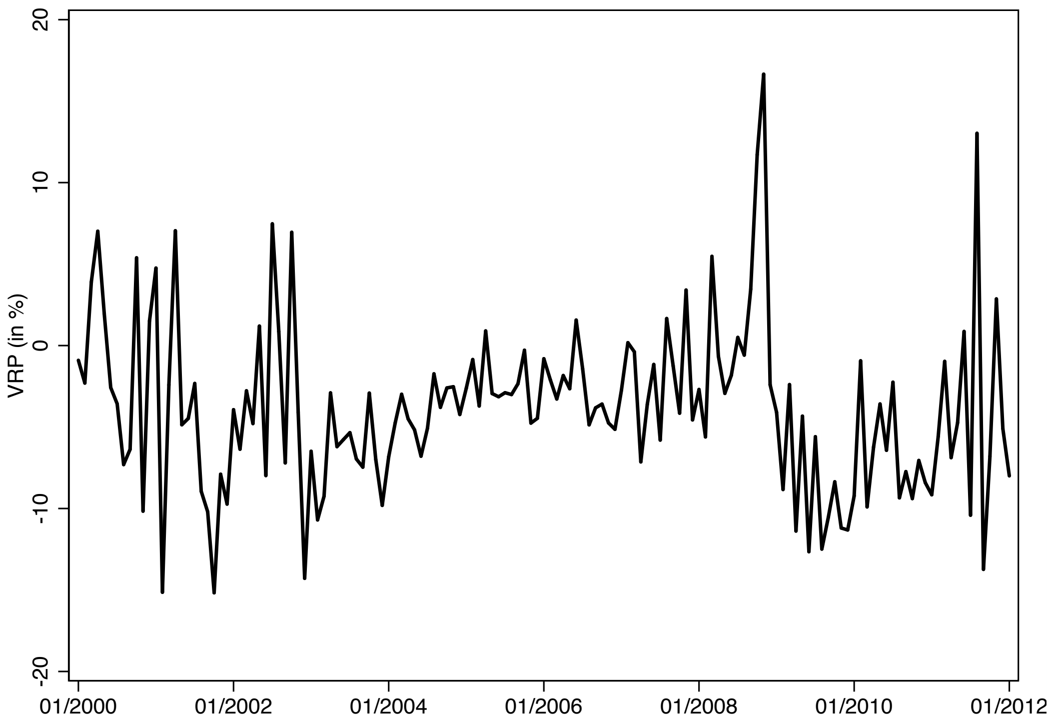
This graphs depicts the aggregate measure of illiquidity of Amihud. We calculate this measure by first taking the AR(2) residuals when regressing aggregate Amihud ratio on its first two lags. The time periods spans from March 2000 to December 2011.

Figure 7: Time series of Risk Aversion



This graphs plots the time series of the time-varying risk aversion under habit preferences based on the consumption surplus ratio. The time period spans from February 1959 to December 2010.

Figure 8: Time series of Variance Risk Premium



This graphs depicts the time series of variance risk premium (VRP). We calculate the VRP by taking the difference between the monthly and realized volatility of the returns of the S&P 500 index (annualized volatility) and the end-of-month value of the VIX index for the corresponding month. The time series spans from January 2000 to January 2012.

A The Aggregate Bid-Ask Spread Illiquidity, the Market-Wide Illiquidity of the Corporate Bond Market, and CDS Spreads

The results contained in Panels A to E of Table A1 show that, when we employ ILB instead of ILS, we find very similar results for all maturities in terms of the relationship between changes of CDS spreads and the behavior of market-wide illiquidity of the CDS market, VRP, and DEF. In fact, the R-squared statistics present similar magnitudes across CDS portfolios and maturities. The relationship between spreads and ILB shows a positive and significant coefficient for the shortest maturities both for the full period and the recession sub-period. As in Table 6 this result only holds for the AAA to A- CDS portfolio. However, the significant spillover effects from the aggregate illiquidity of the equity market to the CDS market reported in Table 6 for the expansion sub-period does not seem to hold for the aggregate illiquidity of the corporate bond market. If anything, for the 5-year maturity, we observe a negative relationship between the illiquidity of corporate bonds and the high quality CDS portfolio spreads. This weaker result of ILB relative to ILS may be explained by the fact that our measure of market-wide illiquidity of corporate bonds only incorporates the 100 largest US companies.

[INSERT TABLE A1 ABOUT HERE]

Table A1: Portfolio CDS Spreads, Aggregate CDS Bid-ask spread and Bond Illiquidity.

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

Panel A: Maturity 1 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−2.09	6.65*	4.54	32.25	−2.82	−12.46	−58.70**	−73.67	10.95	24.17*	23.05	133.97
	(−0.60)	(1.78)	(0.41)	(1.24)	(−0.89)	(−1.45)	(−2.08)	(−0.89)	(1.00)	(2.03)	(0.89)	(1.33)
Δ ILBAS1y	1.08***	0.55*	1.46	11.31***	1.00***	2.59***	10.68***	35.58***	1.24***	0.56*	1.23	11.20***
	(4.74)	(1.97)	(1.58)	(5.58)	(4.85)	(5.00)	(5.82)	(5.96)	(4.25)	(1.99)	(1.12)	(4.62)
ILB	104.33***	19.97	−197.42	−317.70	−6.94***	−5.29	26.70	145.62	130.52**	2.33	−294.84	−482.57
	(2.81)	(0.56)	(−0.90)	(−0.64)	(−2.83)	(−0.40)	(0.54)	(1.17)	(2.67)	(0.05)	(−1.06)	(−0.78)
RA	−0.28	−0.08	0.16	−0.59	0.10	0.45	2.22**	3.05	−0.59*	−0.31	0.01	−2.07
	(−1.49)	(−0.71)	(0.40)	(−0.39)	(0.81)	(1.40)	(2.11)	(0.94)	(−1.85)	(−1.49)	(0.02)	(−0.82)
VRP	−4.04**	1.06	3.83	4.00	−0.00	−0.15	−0.23	2.63	−6.09**	0.87	4.46	0.40
	(−2.28)	(1.08)	(1.05)	(0.35)	(−0.02)	(−0.85)	(−0.30)	(1.37)	(−2.30)	(0.69)	(0.93)	(0.02)
Δ TERM	7.63	−11.49	−14.49	−0.26	0.32	−0.75	−5.43	−9.05	11.90	−22.34*	−34.31	−38.26
	(0.87)	(−1.22)	(−0.77)	(−0.00)	(0.43)	(−0.62)	(−0.78)	(−0.41)	(0.83)	(−1.83)	(−1.37)	(−0.30)
Δ DEF	82.98**	−9.14	166.45**	129.32	7.80***	20.85**	70.68**	53.68	93.48**	−9.53	190.76*	186.45
	(2.59)	(−0.53)	(2.28)	(0.99)	(2.94)	(2.28)	(2.47)	(0.61)	(2.30)	(−0.51)	(2.01)	(1.17)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.467	0.246	0.536	0.477	0.573	0.451	0.470	0.544	0.471	0.219	0.503	0.413

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Maturity 3 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.29	4.95	2.86	45.48*	−8.25	−20.46	−139.32**	−174.21	13.07	22.47*	32.89	160.90*
	(−0.09)	(1.39)	(0.33)	(1.97)	(−1.43)	(−1.41)	(−2.36)	(−1.21)	(1.57)	(1.84)	(1.42)	(1.85)
Δ ILBAS3y	0.84***	0.46*	2.41***	8.61***	0.67***	1.37***	6.87***	10.52	0.92***	0.50**	2.40***	8.77***
	(3.80)	(1.93)	(3.98)	(3.72)	(3.34)	(2.87)	(4.24)	(1.62)	(3.33)	(2.18)	(3.63)	(3.55)
ILB	58.07	−6.22	−136.72	−390.90	−2.44	17.17	172.39**	215.31	64.22	−27.16	−207.33	−545.40
	(1.23)	(−0.19)	(−1.00)	(−1.01)	(−0.40)	(0.70)	(2.24)	(0.95)	(0.98)	(−0.71)	(−1.25)	(−1.18)
RA	−0.22	−0.06	−0.05	−0.74	0.32	0.78	5.44**	7.39	−0.50**	−0.30	−0.47	−2.44
	(−1.60)	(−0.58)	(−0.17)	(−0.56)	(1.37)	(1.41)	(2.37)	(1.34)	(−2.44)	(−1.41)	(−1.07)	(−1.26)
VRP	−2.84**	0.73	0.39	5.77	0.01	−0.10	−0.38	5.65*	−4.35**	0.37	−0.67	1.42
	(−2.45)	(0.74)	(0.19)	(0.69)	(0.11)	(−0.31)	(−0.32)	(1.75)	(−2.72)	(0.27)	(−0.25)	(0.12)
Δ TERM	7.38	−10.45	−12.42	20.09	0.36	−0.60	−5.48	3.61	9.20	−21.62*	−31.83	−24.09
	(0.90)	(−1.18)	(−0.78)	(0.34)	(0.43)	(−0.30)	(−0.81)	(0.15)	(0.77)	(−1.94)	(−1.52)	(−0.27)
Δ DEF	84.52***	24.20	170.07***	224.74***	17.13***	42.15***	161.39***	235.79**	97.12***	26.88	192.89**	275.18***
	(3.83)	(1.51)	(2.75)	(2.67)	(4.91)	(3.72)	(4.33)	(2.18)	(3.53)	(1.42)	(2.47)	(2.85)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.519	0.242	0.581	0.412	0.416	0.233	0.456	0.213	0.529	0.211	0.565	0.355

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Maturity 5 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.40	3.39	3.77	40.25*	−5.45	−8.87	−105.14*	−30.59	12.81	20.54*	28.26	160.37*
	(−0.14)	(0.96)	(0.46)	(1.75)	(−0.61)	(−0.46)	(−1.86)	(−0.19)	(1.65)	(1.73)	(1.12)	(1.98)
Δ ILBAS5y	0.87***	0.56**	2.01**	9.10***	1.29***	3.09***	12.76***	25.99***	0.94***	0.62**	1.97**	9.41***
	(3.57)	(2.06)	(2.51)	(3.54)	(4.76)	(2.94)	(5.98)	(6.30)	(3.29)	(2.35)	(2.27)	(3.50)
ILB	49.32	−9.55	−239.75*	−296.62	−15.32**	−7.49	55.86	−50.35	52.65	−29.03	−321.49*	−434.10
	(1.11)	(−0.29)	(−1.68)	(−0.87)	(−2.49)	(−0.31)	(0.82)	(−0.32)	(0.87)	(−0.75)	(−1.98)	(−1.05)
RA	−0.18	−0.04	0.05	−0.74	0.21	0.32	4.18*	1.70	−0.44**	−0.28	−0.26	−2.56
	(−1.50)	(−0.44)	(0.22)	(−0.65)	(0.60)	(0.43)	(1.91)	(0.27)	(−2.58)	(−1.37)	(−0.61)	(−1.46)
VRP	−2.45**	0.39	1.58	2.93	0.10	−0.10	−0.03	4.64*	−3.79***	−0.04	0.97	−2.31
	(−2.60)	(0.41)	(0.67)	(0.44)	(0.64)	(−0.26)	(−0.03)	(1.92)	(−3.09)	(−0.03)	(0.32)	(−0.23)
Δ TERM	3.52	−13.38	−13.28	−13.12	−0.30	−1.48	−4.22	0.77	3.86	−25.15**	−34.75	−64.41
	(0.44)	(−1.59)	(−0.71)	(−0.28)	(−0.32)	(−0.61)	(−0.39)	(0.03)	(0.34)	(−2.42)	(−1.29)	(−0.94)
Δ DEF	79.14***	31.70*	172.65***	190.30**	21.63***	47.67***	137.57***	90.73	90.59***	34.15*	195.49**	244.56***
	(4.23)	(1.88)	(2.97)	(2.50)	(3.63)	(3.38)	(2.93)	(0.85)	(3.93)	(1.72)	(2.64)	(2.91)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.540	0.254	0.541	0.340	0.488	0.361	0.514	0.376	0.551	0.229	0.536	0.276

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel D: Maturity 7 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	-0.82	1.74	0.76	34.12	-9.75	-20.70	-172.41^{**}	-145.23	11.53	16.14	23.00	148.92^{*}
	(-0.30)	(0.50)	(0.10)	(1.53)	(-1.01)	(-1.43)	(-2.28)	(-1.13)	(1.62)	(1.41)	(0.88)	(1.87)
Δ ILBAS7y	0.82^{***}	0.53^{**}	1.77^{**}	8.96^{***}	1.67^{***}	4.30^{***}	11.31^{**}	29.15^{***}	0.90^{***}	0.59^{**}	1.78^{**}	9.39^{***}
	(4.09)	(2.27)	(2.56)	(3.59)	(4.44)	(3.78)	(2.46)	(3.11)	(3.62)	(2.52)	(2.25)	(3.46)
ILB	45.18	-10.21	-252.07^{*}	-242.50	-3.52	21.07	151.33^{*}	222.44	47.78	-28.35	-324.54^{*}	-377.08
	(1.14)	(-0.31)	(-1.82)	(-0.71)	(-0.44)	(0.90)	(1.73)	(1.03)	(0.88)	(-0.74)	(-2.05)	(-0.91)
RA	-0.16	-0.02	0.09	-0.75	0.38	0.79	6.93^{**}	6.39	-0.41^{**}	-0.22	-0.22	-2.53
	(-1.52)	(-0.21)	(0.41)	(-0.71)	(0.99)	(1.45)	(2.34)	(1.24)	(-2.64)	(-1.11)	(-0.51)	(-1.48)
VRP	-2.34^{***}	0.13	1.02	1.22	0.02	-0.28	0.59	5.28^{*}	-3.60^{***}	-0.27	0.19	-4.55
	(-2.77)	(0.15)	(0.47)	(0.20)	(0.13)	(-1.05)	(0.46)	(1.77)	(-3.21)	(-0.21)	(0.07)	(-0.47)
Δ TERM	2.20	-14.44^{*}	-19.79	-14.86	0.06	-0.89	-11.93	13.80	1.75	-25.77^{**}	-39.05^{*}	-69.75
	(0.31)	(-1.79)	(-1.28)	(-0.33)	(0.08)	(-0.40)	(-1.47)	(0.87)	(0.17)	(-2.52)	(-1.74)	(-1.13)
Δ DEF	73.72^{***}	37.35^{**}	177.67^{***}	176.79^{**}	24.66^{***}	52.88^{***}	195.21^{***}	133.87	84.32^{***}	40.25^{*}	199.14^{**}	236.02^{***}
	(4.32)	(2.07)	(3.14)	(2.48)	(4.87)	(5.26)	(4.59)	(1.19)	(4.01)	(1.86)	(2.77)	(3.18)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.545	0.261	0.524	0.338	0.515	0.491	0.453	0.454	0.557	0.224	0.525	0.277

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel E: Maturity 10 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.19	0.38	−0.52	29.63	−8.83	−18.84	-161.66^{**}	−192.17	9.40	12.19	16.34	116.55
	(−0.47)	(0.11)	(−0.07)	(1.50)	(−0.71)	(−1.25)	(−2.13)	(−1.13)	(1.43)	(1.16)	(0.71)	(1.70)
Δ ILBAS10y	0.86^{***}	0.61^{**}	1.10	9.16^{***}	1.68^{***}	4.09^{***}	13.80^{***}	22.46^{***}	0.94^{***}	0.67^{**}	1.13	9.47^{***}
	(4.40)	(2.52)	(1.64)	(4.03)	(4.03)	(4.16)	(5.91)	(2.83)	(3.87)	(2.70)	(1.49)	(3.84)
ILB	41.70	−8.62	−142.10	−296.64	−1.77	15.90	106.59	188.68	44.05	−25.07	−192.65	−386.29
	(1.06)	(−0.27)	(−1.25)	(−1.07)	(−0.23)	(0.76)	(1.22)	(0.96)	(0.82)	(−0.66)	(−1.41)	(−1.15)
RA	−0.14	0.00	0.07	−0.49	0.35	0.72	6.54^{**}	8.44	-0.35^{**}	−0.16	−0.18	−1.90
	(−1.38)	(0.00)	(0.32)	(−0.57)	(0.71)	(1.25)	(2.19)	(1.24)	(−2.53)	(−0.89)	(−0.46)	(−1.37)
VRP	-2.14^{***}	−0.08	0.37	2.96	0.06	−0.27	0.73	7.53^{**}	-3.27^{***}	−0.40	−0.56	−1.86
	(−2.85)	(−0.09)	(0.20)	(0.66)	(0.40)	(−0.89)	(0.53)	(2.39)	(−3.35)	(−0.34)	(−0.22)	(−0.26)
Δ TERM	1.07	-16.06^{**}	−27.25	−9.84	−0.31	−0.77	−10.45	−21.78	0.67	-27.12^{**}	-44.39^{*}	−37.12
	(0.16)	(−2.14)	(−1.67)	(−0.27)	(−0.37)	(−0.30)	(−1.26)	(−0.70)	(0.07)	(−2.79)	(−1.82)	(−0.75)
Δ DEF	67.11^{***}	38.92^{**}	169.09^{***}	145.32^{**}	22.44^{***}	54.04^{***}	154.33^{***}	189.03	76.85^{***}	41.51^{*}	188.02^{**}	188.98^{**}
	(4.32)	(2.23)	(2.94)	(2.19)	(3.77)	(4.63)	(3.88)	(1.52)	(4.02)	(1.94)	(2.57)	(2.68)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.544	0.287	0.431	0.417	0.471	0.487	0.497	0.342	0.551	0.249	0.411	0.364

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B The Aggregate Gamma Illiquidity Measure, the Market-Wide Illiquidity of the Equity Market, and CDS Spreads

Panels A to E of Table B1 summarizes the regression results with changes in portfolio CDS spreads as the dependent variable, where the aggregate illiquidity measure of the CDS and US stock markets are ILCOV and ILS respectively. Overall, the aggregate gamma measure of illiquidity of the CDS market shows weaker results than the bid-ask spread measure. The positive and significant relationship between changes in CDS spreads and changes in aggregate illiquidity only holds for the BB+ to BB- rated portfolio. There is also a weak positive relationship with the junk CDS portfolio spreads during the expansion sub-period as long as we employ 5-, 7-, and 10- year maturities. The R-squared statistics are systematically lower when we use ILCOV rather than ILBAS reflecting the lower explanatory power of the gamma measure.

[INSERT TABLE B1 ABOUT HERE]

Table B1: Portfolio CDS Spreads, Aggregate CDS Gamma Stock Illiquidity.

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

Panel A: Maturity 1 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.74	4.91*	8.92	44.52*	−5.96	−23.62**	−101.77***	−201.88*	6.26	15.83*	12.28	51.56
	(−0.25)	(1.76)	(1.31)	(1.68)	(−1.44)	(−2.57)	(−3.18)	(−1.88)	(1.00)	(1.83)	(0.49)	(0.76)
Δ ILCOV1y	−5.80	5.34	−2.57	−32.39	−6.70	338.33*	1516.49**	3595.95*	−5.41	3.94	−5.69	−41.25
	(−0.36)	(0.46)	(−0.06)	(−0.12)	(−0.14)	(1.77)	(2.65)	(1.76)	(−0.30)	(0.29)	(−0.13)	(−0.14)
ILS	36.16***	8.53	22.12	168.39	3.56***	8.76**	30.86**	131.26***	40.68**	12.05	23.23	178.65
	(2.93)	(0.62)	(1.08)	(1.03)	(3.21)	(2.48)	(2.60)	(3.37)	(2.60)	(0.74)	(0.89)	(0.89)
RA	−0.14*	−0.02	0.14	0.23	0.23	0.89**	3.91***	8.09*	−0.26**	−0.13	0.17	0.32
	(−1.90)	(−0.46)	(0.83)	(0.36)	(1.41)	(2.56)	(3.25)	(1.93)	(−2.29)	(−1.03)	(0.38)	(0.27)
VRP	−2.53**	1.00	4.79	15.56	0.01	−0.21	−0.33	2.08	−3.39**	0.97	5.71	18.09
	(−2.00)	(1.05)	(1.22)	(1.11)	(0.06)	(−1.23)	(−0.42)	(0.74)	(−2.10)	(0.74)	(1.03)	(0.97)
Δ TERM	2.99	−10.72	−6.59	36.86	0.02	−1.85	−8.52	−14.07	0.70	−20.24*	−13.56	33.08
	(0.33)	(−1.28)	(−0.38)	(0.49)	(0.02)	(−1.10)	(−0.98)	(−0.52)	(0.06)	(−1.76)	(−0.47)	(0.31)
Δ DEF	71.63**	5.83	127.06*	105.56	10.85***	27.18***	96.90***	140.58	74.84**	−2.14	116.26	59.92
	(2.49)	(0.23)	(1.89)	(0.39)	(3.70)	(3.21)	(3.61)	(1.53)	(2.19)	(−0.06)	(1.43)	(0.18)
N	83	83	83	83	41	41	41	41	42	42	42	42
adj. R^2	0.411	0.178	0.385	0.176	0.369	0.360	0.319	0.376	0.397	0.163	0.346	0.108

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Maturity 3 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.65	3.22	4.24	39.55*	−8.41	−19.58	−125.36**	−170.10	6.57	14.44	16.43	61.06
	(−0.27)	(1.21)	(0.75)	(1.83)	(−1.42)	(−1.24)	(−2.10)	(−1.21)	(1.30)	(1.66)	(0.81)	(1.06)
Δ ILCOV3y	−0.36	1.27	6.61	−6.30	3.32	13.63	52.05**	109.52	0.13	1.29	6.90	−6.79
	(−0.14)	(0.52)	(0.75)	(−0.12)	(0.95)	(0.81)	(2.23)	(1.34)	(0.05)	(0.48)	(0.71)	(−0.12)
ILS	30.60***	12.95	40.41	125.36	5.20***	11.27***	39.32***	133.43***	34.15***	15.86	42.64	126.66
	(4.57)	(1.23)	(1.61)	(1.31)	(4.62)	(3.31)	(2.80)	(4.22)	(4.13)	(1.34)	(1.28)	(1.07)
RA	−0.13**	−0.04	−0.06	0.05	0.33	0.75	4.97**	7.24	−0.25***	−0.15	−0.21	−0.12
	(−2.24)	(−0.69)	(−0.52)	(0.11)	(1.42)	(1.27)	(2.13)	(1.34)	(−2.81)	(−1.18)	(−0.61)	(−0.13)
VRP	−2.28**	0.26	0.11	11.29	0.01	−0.14	0.15	4.14	−3.20***	−0.01	−0.46	11.90
	(−2.57)	(0.27)	(0.04)	(1.08)	(0.14)	(−0.43)	(0.13)	(1.47)	(−2.79)	(−0.01)	(−0.11)	(0.81)
Δ TERM	2.32	−11.90	−6.58	27.33	−0.26	−1.11	−4.97	2.96	0.35	−20.93*	−13.15	21.31
	(0.37)	(−1.39)	(−0.31)	(0.43)	(−0.26)	(−0.54)	(−0.57)	(0.10)	(0.05)	(−1.87)	(−0.38)	(0.22)
Δ DEF	61.87***	20.57	123.94**	121.36	17.42***	40.97***	161.69***	214.74**	65.86**	15.46	122.30**	103.25
	(3.04)	(0.93)	(2.36)	(0.67)	(4.32)	(4.47)	(4.08)	(2.45)	(2.61)	(0.56)	(2.06)	(0.46)
N	83	83	83	83	41	41	41	41	42	42	42	42
adj. R^2	0.517	0.240	0.402	0.181	0.518	0.345	0.405	0.457	0.520	0.227	0.358	0.108

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Maturity 5 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.12	1.90	2.52	29.89*	−10.76	−19.19	−140.18**	−116.43	6.76	13.55	14.49	63.34
	(−0.51)	(0.74)	(0.44)	(1.69)	(−1.24)	(−0.98)	(−2.05)	(−0.75)	(1.44)	(1.61)	(0.72)	(1.20)
Δ ILCOV5y	0.25	1.07	5.72***	2.05	1.40	7.01	27.22**	61.56*	0.51	1.17	5.99***	2.59
	(0.29)	(1.23)	(3.56)	(0.10)	(0.81)	(1.05)	(2.11)	(1.83)	(0.53)	(1.25)	(3.07)	(0.12)
ILS	29.19***	13.22	39.68*	108.51	7.26***	12.55***	44.57***	103.75***	32.45***	15.98	41.03	110.42
	(5.24)	(1.37)	(1.82)	(1.30)	(5.49)	(3.43)	(3.42)	(2.95)	(4.65)	(1.46)	(1.39)	(1.06)
RA	−0.13**	−0.05	−0.11	−0.23	0.43	0.73	5.58**	5.07	−0.25***	−0.18	−0.28	−0.64
	(−2.42)	(−1.01)	(−1.08)	(−0.66)	(1.25)	(0.99)	(2.07)	(0.82)	(−3.08)	(−1.51)	(−0.90)	(−0.83)
VRP	−2.44***	−0.38	−1.39	4.08	0.01	−0.28	−0.40	3.06	−3.40***	−0.82	−2.26	2.35
	(−3.03)	(−0.44)	(−0.62)	(0.53)	(0.04)	(−0.68)	(−0.35)	(0.89)	(−3.28)	(−0.66)	(−0.65)	(0.21)
Δ TERM	0.59	−13.69*	−6.69	13.42	−0.75	−1.79	−2.34	−1.58	−1.91	−22.79**	−13.26	3.66
	(0.11)	(−1.72)	(−0.31)	(0.21)	(−0.77)	(−0.82)	(−0.25)	(−0.08)	(−0.28)	(−2.18)	(−0.38)	(0.04)
Δ DEF	59.48***	28.02	109.11*	149.21	25.30***	54.19***	166.61***	143.52	63.99***	24.49	111.16*	154.90
	(3.67)	(1.35)	(1.93)	(1.07)	(4.66)	(4.83)	(3.60)	(1.57)	(3.13)	(0.98)	(1.71)	(0.96)
N	83	83	83	83	41	41	41	41	42	42	42	42
adj. R^2	0.555	0.280	0.452	0.128	0.591	0.379	0.430	0.401	0.570	0.278	0.421	0.052

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel D: Maturity 7 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.16	1.19	1.35	27.08	−10.38	−20.09	−165.29**	−140.80	5.93	11.16	11.08	51.17
	(−0.57)	(0.50)	(0.24)	(1.59)	(−0.97)	(−1.12)	(−2.18)	(−1.07)	(1.33)	(1.37)	(0.55)	(1.03)
Δ ILCOV7y	0.20	0.81	4.62***	−1.82	0.69	6.34	16.96**	35.18**	0.34	0.88	4.84***	−1.55
	(0.28)	(1.10)	(3.05)	(−0.11)	(0.59)	(1.43)	(2.64)	(2.37)	(0.43)	(1.10)	(2.76)	(−0.09)
ILS	27.02***	12.88	29.02	123.52	7.55***	12.56***	39.16**	125.19***	29.98***	15.30	29.49	125.69
	(4.95)	(1.33)	(1.35)	(1.35)	(5.98)	(3.67)	(2.72)	(3.44)	(4.37)	(1.40)	(1.03)	(1.13)
RA	−0.11**	−0.04	−0.08	−0.13	0.42	0.77	6.65**	6.25	−0.22***	−0.15	−0.22	−0.42
	(−2.40)	(−0.85)	(−0.89)	(−0.36)	(0.99)	(1.13)	(2.21)	(1.19)	(−3.07)	(−1.34)	(−0.77)	(−0.55)
VRP	−2.24***	−0.48	−1.23	4.62	−0.01	−0.38	0.28	4.07	−3.05***	−0.85	−2.06	3.44
	(−3.01)	(−0.56)	(−0.60)	(0.56)	(−0.07)	(−0.98)	(0.21)	(1.14)	(−3.21)	(−0.71)	(−0.66)	(0.30)
Δ TERM	−0.36	−14.62*	−14.04	7.92	−0.51	−1.57	−10.28	12.65	−3.07	−23.32**	−18.84	−4.11
	(−0.07)	(−1.98)	(−0.69)	(0.12)	(−0.49)	(−0.72)	(−1.00)	(0.85)	(−0.46)	(−2.37)	(−0.57)	(−0.04)
Δ DEF	53.87***	29.64	110.02**	100.90	27.81***	56.86***	203.14***	160.64	57.27***	26.23	112.53*	100.99
	(3.95)	(1.46)	(2.09)	(0.71)	(4.43)	(5.11)	(4.82)	(1.65)	(3.31)	(1.08)	(1.86)	(0.60)
N	83	83	83	83	41	41	41	41	42	42	42	42
adj. R^2	0.557	0.293	0.426	0.115	0.533	0.448	0.432	0.525	0.569	0.285	0.396	0.033

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel E: Maturity 10 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.40	0.55	0.98	22.03	−11.11	−22.05	-168.24^{**}	−213.42	5.36	9.32	10.12	38.21
	(−0.75)	(0.25)	(0.19)	(1.54)	(−0.85)	(−1.16)	(−2.26)	(−1.33)	(1.30)	(1.22)	(0.52)	(0.85)
Δ ILCOV10y	0.41	0.61	1.67^{***}	3.25	0.93	3.94	14.14^{**}	23.61^{**}	0.50	0.66	1.83^{**}	3.56
	(1.01)	(1.43)	(2.69)	(0.38)	(0.90)	(1.31)	(2.71)	(2.29)	(1.12)	(1.41)	(2.34)	(0.39)
ILS	26.38^{***}	13.86	19.82	118.50	7.97^{***}	12.30^{***}	37.47^{**}	125.94^{***}	29.29^{***}	16.53	19.20	116.47
	(5.71)	(1.50)	(0.98)	(1.63)	(6.09)	(3.35)	(2.69)	(3.71)	(4.97)	(1.58)	(0.70)	(1.30)
RA	-0.11^{**}	−0.04	−0.05	−0.17	0.45	0.86	6.84^{**}	9.25	-0.22^{***}	−0.14	−0.18	−0.43
	(−2.50)	(−0.91)	(−0.52)	(−0.61)	(0.87)	(1.19)	(2.30)	(1.46)	(−3.17)	(−1.33)	(−0.67)	(−0.70)
VRP	-2.27^{***}	−0.67	−0.75	2.55	−0.01	−0.33	0.65	5.58	-3.07^{***}	−1.02	−1.55	0.79
	(−3.37)	(−0.84)	(−0.40)	(0.43)	(−0.03)	(−0.86)	(0.51)	(1.44)	(−3.57)	(−0.93)	(−0.55)	(0.09)
Δ TERM	−1.11	-15.77^{**}	−26.10	15.86	−0.78	−1.28	−10.34	−20.66	−3.78	-24.42^{**}	−34.51	24.29
	(−0.24)	(−2.31)	(−1.48)	(0.25)	(−0.76)	(−0.56)	(−0.96)	(−0.61)	(−0.62)	(−2.63)	(−1.19)	(0.26)
Δ DEF	48.04^{***}	30.09	125.95^{**}	68.82	26.79^{***}	63.06^{***}	183.62^{***}	221.43^{**}	51.32^{***}	26.23	131.35^{**}	80.90
	(4.09)	(1.50)	(2.56)	(0.58)	(3.84)	(5.24)	(5.15)	(2.53)	(3.42)	(1.11)	(2.26)	(0.61)
N	83	83	83	83	41	41	41	41	42	42	42	42
adj. R^2	0.581	0.317	0.395	0.159	0.531	0.443	0.433	0.479	0.599	0.310	0.374	0.081

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C The Aggregate Gamma Illiquidity Measure, the Market-Wide Illiquidity of the Corporate Bond Market, and CDS Spreads

Panels A to E of Table C1 present the empirical results using the gamma measure and the market-wide illiquidity of the corporate bond market instead the illiquidity of the equity market. As before, the gamma measure shows lower explanatory power than the bid-ask spread measure even when we use illiquidity from corporate bonds. However, the positive effects reported between CDS spreads of high quality bonds and ILB does not hold anymore. On the contrary, we now find a negative and significant relationship between changes of CDS spreads of junk portfolios and ILB. When there is an increase of aggregate illiquidity in the bond market of large companies, the CDS spread on junk bonds diminishes.

[INSERT TABLE C1 ABOUT HERE]

Table C1: Portfolio CDS Spreads, Aggregate CDS Gamma and Amihud Bond Illiquidity.

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

Panel A: Maturity 1 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.25	7.87**	7.67	56.46**	−5.29	−22.23**	−99.14**	−192.74	12.67	25.68**	21.79	130.30
	(0.07)	(2.12)	(0.73)	(2.08)	(−1.06)	(−2.06)	(−2.72)	(−1.44)	(1.21)	(2.10)	(0.72)	(1.48)
Δ ILCOV1y	4.74	7.31	0.58	4.15	3.35	351.99*	1471.69**	3322.23	8.94	7.23	−3.97	−2.37
	(0.47)	(0.79)	(0.02)	(0.02)	(0.07)	(2.00)	(2.49)	(1.62)	(0.89)	(0.73)	(−0.13)	(−0.01)
ILB	−1.86	−32.74	−342.15**	−1436.22***	−2.33	−0.01	48.01	247.20*	−6.89	−58.35	−435.75**	−1756.18***
	(−0.03)	(−0.89)	(−2.02)	(−2.87)	(−0.44)	(−0.00)	(0.71)	(1.88)	(−0.10)	(−1.40)	(−2.26)	(−3.06)
RA	−0.21	−0.07	0.28	0.35	0.21	0.85**	3.84**	7.90	−0.49*	−0.29	0.23	−0.39
	(−1.19)	(−0.61)	(0.74)	(0.25)	(1.04)	(2.04)	(2.72)	(1.48)	(−1.79)	(−1.39)	(0.36)	(−0.20)
VRP	−2.44*	1.62	6.30*	23.11*	0.10	0.02	0.46	5.41**	−4.17**	1.50	7.33	24.04
	(−1.77)	(1.64)	(1.70)	(1.94)	(1.36)	(0.13)	(0.57)	(2.16)	(−2.08)	(1.09)	(1.42)	(1.45)
Δ TERM	14.48	−6.90	−6.57	60.84	0.06	−1.94	−10.33	−23.13	19.81	−17.72	−30.72	5.75
	(1.27)	(−0.85)	(−0.43)	(0.95)	(0.05)	(−1.12)	(−1.16)	(−0.92)	(1.22)	(−1.69)	(−1.41)	(0.06)
Δ DEF	127.66***	12.97	227.42***	600.54***	11.56***	29.02**	104.23**	172.55	147.19***	14.78	243.44***	668.73***
	(3.49)	(0.82)	(3.81)	(4.59)	(2.96)	(2.53)	(2.68)	(1.47)	(3.10)	(0.86)	(3.43)	(3.71)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.323	0.176	0.478	0.262	0.129	0.178	0.193	0.127	0.285	0.142	0.460	0.191

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Maturity 3 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	0.22	5.11	3.82	53.63*	−7.19	−18.43	−128.49*	−159.31	11.28	21.66	28.60	120.73*
	(0.06)	(1.41)	(0.40)	(1.98)	(−0.95)	(−1.09)	(−1.95)	(−1.04)	(1.45)	(1.71)	(1.12)	(1.77)
Δ ILCOV3y	0.62	1.19	5.28	−14.63	7.37*	21.31	73.45***	198.26**	1.83	1.23	5.35	−16.90
	(0.25)	(0.46)	(0.58)	(−0.27)	(1.83)	(1.21)	(2.91)	(2.21)	(0.66)	(0.42)	(0.53)	(−0.29)
ILB	2.03	−33.53	−282.86*	−1053.91**	−6.05	8.75	135.82*	144.81	3.13	−59.03	−364.00**	−1295.59**
	(0.04)	(−0.95)	(−1.95)	(−2.09)	(−0.99)	(0.34)	(1.81)	(0.66)	(0.05)	(−1.41)	(−2.12)	(−2.17)
RA	−0.16	−0.04	0.06	0.21	0.29	0.71	5.13*	6.88	−0.42**	−0.26	−0.28	−0.51
	(−1.29)	(−0.47)	(0.27)	(0.20)	(0.95)	(1.10)	(1.96)	(1.15)	(−2.34)	(−1.13)	(−0.59)	(−0.34)
VRP	−1.97*	1.00	2.01	19.83*	0.13	0.09	0.86	6.86**	−3.59***	0.70	1.12	20.44
	(−1.98)	(0.90)	(0.71)	(1.81)	(1.23)	(0.28)	(0.78)	(2.44)	(−2.91)	(0.39)	(0.26)	(1.31)
Δ TERM	11.29	−7.85	0.62	49.35	−0.10	−1.53	−10.17	−3.47	15.37	−18.08	−15.22	5.07
	(1.19)	(−0.96)	(0.04)	(0.91)	(−0.10)	(−0.70)	(−1.07)	(−0.14)	(1.16)	(−1.69)	(−0.79)	(0.06)
Δ DEF	108.89***	37.62**	240.05***	475.00***	17.66***	41.94***	167.15***	227.04*	125.41***	42.34*	267.11***	521.00***
	(4.33)	(2.22)	(4.12)	(3.75)	(3.61)	(3.54)	(3.77)	(2.00)	(3.94)	(2.01)	(3.77)	(3.10)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.397	0.191	0.436	0.248	0.294	0.196	0.329	0.208	0.379	0.144	0.402	0.169

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Maturity 5 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.64	3.06	2.24	41.14	−9.22	−18.03	−142.33*	−107.62	11.00	19.70	27.19	121.02**
	(−0.20)	(0.85)	(0.25)	(1.53)	(−0.85)	(−0.85)	(−1.86)	(−0.59)	(1.43)	(1.66)	(1.05)	(2.09)
Δ ILCOV5y	0.84	1.08	4.84**	−1.37	3.96	10.89	38.72**	93.38**	1.43	1.21	4.97*	−1.12
	(0.98)	(1.09)	(2.47)	(−0.06)	(1.67)	(1.46)	(2.47)	(2.34)	(1.53)	(1.06)	(2.06)	(−0.05)
ILB	11.32	−27.33	−292.52**	−817.20	−8.56	7.87	122.94	77.57	16.23	−49.56	−370.50**	−1009.16
	(0.27)	(−0.73)	(−2.19)	(−1.60)	(−1.06)	(0.26)	(1.41)	(0.36)	(0.32)	(−1.10)	(−2.41)	(−1.64)
RA	−0.16	−0.05	0.02	−0.14	0.36	0.68	5.66*	4.70	−0.42**	−0.28	−0.36	−1.28
	(−1.36)	(−0.53)	(0.07)	(−0.17)	(0.84)	(0.83)	(1.86)	(0.64)	(−2.62)	(−1.35)	(−0.80)	(−1.21)
VRP	−2.23**	0.24	0.57	10.50	0.12	−0.10	0.21	4.59	−3.91***	−0.30	−0.70	7.52
	(−2.43)	(0.23)	(0.24)	(1.21)	(0.64)	(−0.21)	(0.17)	(1.34)	(−3.72)	(−0.18)	(−0.20)	(0.61)
Δ TERM	9.08	−9.51	1.17	39.40	−0.66	−2.42	−7.79	−7.18	12.53	−19.13**	−14.49	5.07
	(1.08)	(−1.28)	(0.08)	(0.74)	(−0.64)	(−0.93)	(−0.69)	(−0.32)	(1.09)	(−2.08)	(−0.70)	(0.07)
Δ DEF	102.91***	46.67***	226.10***	444.46***	24.67***	53.78***	167.92***	140.44	118.64***	52.93**	255.62***	512.39***
	(4.93)	(2.78)	(3.94)	(4.58)	(3.61)	(3.98)	(3.12)	(1.11)	(4.58)	(2.57)	(3.64)	(4.25)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.428	0.213	0.503	0.158	0.363	0.261	0.334	0.230	0.429	0.168	0.498	0.059

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel D: Maturity 7 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−0.95	1.51	−0.24	37.55	−8.67	−18.32	-166.06^{*}	−128.63	9.63	15.37	22.14	98.47
	(−0.32)	(0.43)	(−0.03)	(1.47)	(−0.67)	(−0.93)	(−2.00)	(−0.74)	(1.35)	(1.36)	(0.88)	(1.69)
Δ ILCOV7y	0.85	0.98	3.99^{**}	−4.99	2.02	8.24^{*}	21.02^{***}	52.49^{***}	1.23	1.09	4.10^{*}	−5.18
	(1.07)	(1.07)	(2.06)	(−0.25)	(1.50)	(1.76)	(3.17)	(2.85)	(1.39)	(1.03)	(1.77)	(−0.24)
ILB	9.64	−26.22	-295.42^{**}	−846.12	−9.89	0.07	97.08	85.16	12.47	−46.79	-365.98^{**}	−1043.81
	(0.25)	(−0.67)	(−2.18)	(−1.61)	(−1.24)	(0.00)	(1.20)	(0.48)	(0.26)	(−0.99)	(−2.33)	(−1.68)
RA	−0.14	−0.02	0.07	0.01	0.35	0.70	6.70^{*}	5.80	-0.37^{**}	−0.21	−0.27	−0.81
	(−1.34)	(−0.23)	(0.36)	(0.02)	(0.68)	(0.91)	(2.01)	(0.83)	(−2.56)	(−1.09)	(−0.66)	(−0.72)
VRP	-2.09^{**}	0.05	0.38	11.65	0.13	−0.15	0.98	6.38^{*}	-3.50^{***}	−0.41	−0.86	9.72
	(−2.55)	(0.05)	(0.17)	(1.30)	(0.71)	(−0.36)	(0.77)	(1.72)	(−3.69)	(−0.28)	(−0.27)	(0.77)
Δ TERM	6.90	-11.49^{*}	−9.96	37.96	−0.27	−1.75	−14.19	7.97	8.85	-21.09^{**}	−24.91	2.52
	(0.94)	(−1.67)	(−0.77)	(0.61)	(−0.24)	(−0.68)	(−1.39)	(0.44)	(0.85)	(−2.54)	(−1.47)	(0.03)
Δ DEF	93.67^{***}	49.14^{***}	215.76^{***}	425.20^{***}	27.79^{***}	57.35^{***}	207.77^{***}	168.25	107.09^{***}	54.92^{**}	242.42^{***}	489.78^{***}
	(4.99)	(2.92)	(4.09)	(3.45)	(3.77)	(4.40)	(4.39)	(1.26)	(4.56)	(2.70)	(3.75)	(3.16)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.430	0.228	0.501	0.150	0.319	0.333	0.365	0.280	0.426	0.174	0.500	0.048

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel E: Maturity 10 year

	01/2004 to 04/2011				01/2004 to 06/2007				07/2007 to 04/2011			
	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D	AAA to A-	BBB+ to BBB-	BB+ to BB-	B+ to D
Cons	−1.52	0.09	−1.00	29.47	−9.32	−20.05	−165.74*	−199.02	8.00	11.17	14.56	81.05
	(−0.55)	(0.03)	(−0.12)	(1.29)	(−0.61)	(−0.96)	(−1.98)	(−1.06)	(1.16)	(1.07)	(0.63)	(1.56)
Δ ILCOV10y	0.87**	0.73	1.23	1.91	1.85	5.22	17.39***	35.60***	1.11**	0.79	1.31	2.10
	(2.07)	(1.46)	(1.13)	(0.18)	(1.56)	(1.62)	(3.00)	(2.75)	(2.37)	(1.36)	(0.97)	(0.19)
ILB	10.24	−28.15	−179.66	−783.14*	−7.96	−0.72	51.01	82.52	12.72	−47.64	−231.33	−909.96*
	(0.29)	(−0.79)	(−1.52)	(−1.82)	(−0.95)	(−0.03)	(0.60)	(0.41)	(0.28)	(−1.09)	(−1.63)	(−1.80)
RA	−0.12	0.01	0.08	−0.01	0.38	0.79	6.75*	8.72	−0.33**	−0.15	−0.16	−0.85
	(−1.25)	(0.07)	(0.41)	(−0.01)	(0.63)	(0.97)	(2.01)	(1.15)	(−2.49)	(−0.82)	(−0.39)	(−0.99)
VRP	−2.09***	−0.13	0.36	8.73	0.15	−0.09	1.35	7.99**	−3.41***	−0.50	−0.69	5.60
	(−2.78)	(−0.14)	(0.17)	(1.46)	(0.73)	(−0.22)	(1.08)	(2.06)	(−4.08)	(−0.36)	(−0.22)	(0.66)
Δ TERM	5.59	−12.94**	−21.55	41.23	−0.57	−1.37	−12.49	−24.75	7.37	−22.31***	−36.28*	33.62
	(0.80)	(−2.05)	(−1.47)	(0.76)	(−0.52)	(−0.51)	(−1.10)	(−0.82)	(0.75)	(−2.88)	(−1.72)	(0.46)
Δ DEF	86.89***	52.47***	193.93***	375.55***	26.86***	63.50***	186.59***	228.72*	99.84***	58.00**	215.82***	431.55***
	(5.30)	(3.17)	(3.64)	(4.18)	(3.48)	(4.72)	(4.15)	(1.84)	(4.90)	(2.79)	(3.21)	(3.77)
N	71	71	71	71	41	41	41	41	30	30	30	30
adj. R^2	0.440	0.241	0.406	0.190	0.315	0.341	0.362	0.300	0.441	0.182	0.381	0.091

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D Flight-to-Liquidity/Flight-to Quality under Alternative Measures of Market-Wide Illiquidity

Tables D1 to D3 show the results using the difference between CDS spreads of junk portfolios and CDS spreads of the AAA to A- portfolio. This is the analysis of flight-to-liquidity during the recession sub-period using alternative measures of aggregate illiquidity for both the CDS market and the corporate bond market.

[INSERT TABLE D1 to D3 ABOUT HERE]

Tables D4 to D6 show similar evidence about flight-to-quality in the stress sub-period. As before, we find a significant flight-to-liquidity but it seems even stronger when we use the aggregate bond illiquidity measure instead of the equity illiquidity. This is also true when we employ the gamma measure of illiquidity. Finally, as in Section 4, we do not find any support of flight-to-quality except for weak evidence at the shortest horizon when we employ the gamma measure and aggregate illiquidity from the bond market.

[INSERT TABLE D4 to D6 ABOUT HERE]

Table D1: Extreme Portfolio CDS Spreads, CDS Bid-Ask Illiquidity and Amihud Bond Illiquidity.

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependant variable. Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	33.97	120.62	46.44	143.90*	47.61	145.41*	37.41	133.94*	19.75	103.46
	(0.55)	(1.31)	(0.94)	(1.82)	(1.07)	(1.97)	(0.86)	(1.85)	(0.49)	(1.67)
RA	−0.85	−4.56	−1.00	−5.05	−0.97	−5.21*	−0.36	−4.53	0.45	−3.15
	(−0.36)	(−1.26)	(−0.51)	(−1.63)	(−0.55)	(−1.79)	(−0.21)	(−1.58)	(0.28)	(−1.28)
RA×D_t	1.61	3.11	1.22	3.17	0.85	3.14*	0.31	2.46	−0.27	1.66
	(0.73)	(1.34)	(0.71)	(1.49)	(0.57)	(1.71)	(0.22)	(1.39)	(−0.21)	(1.07)
VRP	7.16**	3.08*	9.02***	6.74**	8.32**	4.90**	9.68***	6.14**	11.11***	8.29**
	(2.13)	(1.78)	(2.99)	(2.28)	(2.60)	(2.07)	(3.03)	(2.09)	(3.06)	(2.61)
VRP×D_t	16.48	3.46	7.07	−0.89	1.07	−3.37	−1.35	−7.01	−2.13	−6.79
	(0.89)	(0.21)	(0.51)	(−0.08)	(0.09)	(−0.34)	(−0.12)	(−0.72)	(−0.21)	(−0.87)
Δ TERM	−0.47	−0.72	10.34	16.44	7.90	8.65	19.79	25.54	−11.95	−8.72
	(−0.02)	(−0.03)	(0.44)	(0.60)	(0.39)	(0.30)	(1.12)	(1.37)	(−0.37)	(−0.24)
Δ TERM×D_t	80.76	−49.09	40.58	−49.13	19.69	−76.57	5.43	−96.47	69.16	−28.46
	(0.54)	(−0.40)	(0.36)	(−0.55)	(0.20)	(−1.11)	(0.06)	(−1.65)	(0.68)	(−0.49)
Δ DEF	153.50	19.92	225.60**	185.01	174.04	44.41	182.80	79.94	236.75**	132.49
	(1.35)	(0.23)	(2.16)	(1.55)	(1.62)	(0.44)	(1.59)	(0.79)	(2.02)	(1.06)
Δ DEF×D_t	17.54	73.29	−56.81	−6.39	15.54	109.93	−8.88	72.34	−96.65	−19.73
	(0.08)	(0.47)	(−0.30)	(−0.04)	(0.09)	(0.90)	(−0.05)	(0.61)	(−0.59)	(−0.14)
ILB		126.20		180.41		−61.51		194.43		158.31
		(1.01)		(0.74)		(−0.35)		(0.83)		(0.75)
ILB×D_t		−738.36		−788.97		−424.72		−618.52		−587.86
		(−1.20)		(−1.58)		(−0.99)		(−1.35)		(−1.57)
Δ ILBAS1y		35.65***								
		(6.60)								
Δ ILBAS1y×D_t		−25.69***								
		(−4.46)								
Δ ILBAS3y				9.14						
				(1.54)						
Δ ILBAS3y×D_t				−1.29						
				(−0.20)						
Δ ILBAS5y						25.77***				
						(5.28)				
Δ ILBAS5y×D_t						−17.31***				
						(−3.21)				
Δ ILBAS7y								26.91***		
								(2.91)		
Δ ILBAS7y×D_t								−18.43*		
								(−1.93)		
Δ ILBAS10y										20.96***
										(2.84)
Δ ILBAS10y×D_t										−12.44
										(−1.62)
N	83	71	83	71	83	71	83	71	83	71
adj. R^2	0.109	0.418	0.103	0.346	0.043	0.266	0.026	0.271	0.047	0.354

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D2: Extreme Portfolio CDS Spreads, CDS Gamma Illiquidity and Amihud Stock Illiquidity.

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependant variable. Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	33.97	43.58	46.44	52.92	47.61	55.40	37.41	43.95	19.75	31.13
	(0.55)	(0.68)	(0.94)	(0.98)	(1.07)	(1.12)	(0.86)	(0.95)	(0.49)	(0.74)
RA	−0.85	−1.50	−1.00	−1.50	−0.97	−1.66	−0.36	−0.99	0.45	−0.34
	(−0.36)	(−0.60)	(−0.51)	(−0.71)	(−0.55)	(−0.85)	(−0.21)	(−0.54)	(0.28)	(−0.21)
RA×D_t	1.61	2.09	1.22	1.64	0.85	1.28	0.31	0.80	−0.27	0.14
	(0.73)	(0.97)	(0.71)	(0.95)	(0.57)	(0.84)	(0.22)	(0.55)	(−0.21)	(0.11)
VRP	7.16**	2.92	9.02***	4.80*	8.32**	3.58	9.68***	4.65	11.11***	6.31*
	(2.13)	(1.09)	(2.99)	(1.89)	(2.60)	(1.10)	(3.03)	(1.36)	(3.06)	(1.69)
VRP×D_t	16.48	18.58	7.07	10.33	1.07	2.19	−1.35	1.86	−2.13	−2.43
	(0.89)	(1.01)	(0.51)	(0.70)	(0.09)	(0.19)	(−0.12)	(0.16)	(−0.21)	(−0.26)
Δ TERM	−0.47	−3.66	10.34	11.93	7.90	5.75	19.79	20.26	−11.95	−10.42
	(−0.02)	(−0.13)	(0.44)	(0.43)	(0.39)	(0.27)	(1.12)	(1.36)	(−0.37)	(−0.29)
Δ TERM×D_t	80.76	36.53	40.58	9.47	19.69	0.15	5.43	−20.94	69.16	38.98
	(0.54)	(0.35)	(0.36)	(0.10)	(0.20)	(0.00)	(0.06)	(−0.20)	(0.68)	(0.39)
Δ DEF	153.50	104.87	225.60**	173.32*	174.04	100.70	182.80	113.74	236.75**	168.38*
	(1.35)	(1.06)	(2.16)	(1.78)	(1.62)	(1.11)	(1.59)	(1.31)	(2.02)	(1.83)
Δ DEF×D_t	17.54	−119.26	−56.81	−135.45	15.54	−9.43	−8.88	−69.65	−96.65	−138.31
	(0.08)	(−0.34)	(−0.30)	(−0.56)	(0.09)	(−0.05)	(−0.05)	(−0.36)	(−0.59)	(−0.84)
ILS		125.65***		126.31***		95.20***		116.21***		115.81***
		(3.47)		(4.23)		(2.92)		(3.39)		(3.72)
ILS×D_t		12.14		−33.96		−17.35		−20.61		−28.78
		(0.06)		(−0.29)		(−0.17)		(−0.18)		(−0.32)
Δ ILCOV1y		3172.98*								
		(1.70)								
Δ ILCOV1y×D_t		−3208.83*								
		(−1.70)								
Δ ILCOV3y				104.31						
				(1.53)						
Δ ILCOV3y×D_t				−111.23						
				(−1.28)						
Δ ILCOV5y						59.18*				
						(1.97)				
Δ ILCOV5y×D_t						−57.10				
						(−1.59)				
Δ ILCOV7y								33.86***		
								(2.94)		
Δ ILCOV7y×D_t								−35.76*		
								(−1.73)		
Δ ILCOV10y										22.53***
										(2.89)
Δ ILCOV10y×D_t										−19.48*
										(−1.68)
N	83	83	83	83	83	83	83	83	83	83
adj. R^2	0.109	0.082	0.103	0.075	0.043	0.011	0.026	0.000	0.047	0.048

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Extreme Portfolio CDS Spreads, CDS Gamma Illiquidity and Amihud Bond Illiquidity.

This table reports monthly regressions with changes in extreme-portfolio CDS spread with different maturities as a dependant variable. Extreme-portfolio CDS spreads are calculated as the difference between CDS spreads of AAA to A- and B to D CDS portfolios. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS(M)y$ denotes changes in aggregate CDS Bid-ask spread with M year maturity (in annual basis points). $\Delta ILCOV(M)y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with M year maturity. ILS and ILB denotes the aggregate Amihud measures of illiquidity for the US stock and bond markets, respectively. RA denotes the time-varying risk aversion under habit preferences based on the consumption surplus ratio. VRP denotes the level of variance risk premium. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	33.97	113.80	46.44	106.14*	47.61	107.39**	37.41	86.19	19.75	69.72
	(0.55)	(1.42)	(0.94)	(1.69)	(1.07)	(2.06)	(0.86)	(1.65)	(0.49)	(1.52)
RA	−0.85	−4.09	−1.00	−3.51	−0.97	−3.72*	−0.36	−2.62	0.45	−1.82
	(−0.36)	(−1.32)	(−0.51)	(−1.47)	(−0.55)	(−1.83)	(−0.21)	(−1.29)	(0.28)	(−1.02)
RA×D_t	1.61	4.24*	1.22	3.48*	0.85	2.90*	0.31	2.22	−0.27	1.36
	(0.73)	(1.81)	(0.71)	(1.78)	(0.57)	(1.70)	(0.22)	(1.34)	(−0.21)	(0.98)
VRP	7.16**	6.32**	9.02***	7.50***	8.32**	5.12	9.68***	6.88*	11.11***	8.60**
	(2.13)	(2.30)	(2.99)	(2.71)	(2.60)	(1.53)	(3.03)	(1.86)	(3.06)	(2.22)
VRP×D_t	16.48	21.98	7.07	16.60	1.07	6.37	−1.35	6.40	−2.13	0.48
	(0.89)	(1.39)	(0.51)	(1.08)	(0.09)	(0.51)	(−0.12)	(0.50)	(−0.21)	(0.05)
Δ TERM	−0.47	−9.33	10.34	8.08	7.90	2.66	19.79	17.38	−11.95	−12.68
	(−0.02)	(−0.30)	(0.44)	(0.29)	(0.39)	(0.10)	(1.12)	(0.90)	(−0.37)	(−0.35)
Δ TERM×D_t	80.76	−4.28	40.58	−17.96	19.69	−9.76	5.43	−23.33	69.16	39.41
	(0.54)	(−0.04)	(0.36)	(−0.21)	(0.20)	(−0.13)	(0.06)	(−0.28)	(0.68)	(0.50)
Δ DEF	153.50	128.83	225.60**	179.94	174.04	92.94	182.80	117.24	236.75**	171.90
	(1.35)	(1.06)	(2.16)	(1.50)	(1.62)	(0.77)	(1.59)	(1.00)	(2.02)	(1.40)
Δ DEF×D_t	17.54	393.05**	−56.81	215.92	15.54	301.04*	−8.88	265.71	−96.65	160.14
	(0.08)	(2.04)	(−0.30)	(1.10)	(0.09)	(1.82)	(−0.05)	(1.42)	(−0.59)	(0.96)
ILB		225.67		122.12		63.64		72.64		61.33
		(1.42)		(0.52)		(0.28)		(0.37)		(0.28)
ILB×D_t		−1973.55***		−1419.82**		−1088.28*		−1128.21*		−983.08*
		(−3.61)		(−2.36)		(−1.75)		(−1.86)		(−1.92)
Δ ILCOV1y		2821.86								
		(1.35)								
Δ ILCOV1y×D_t		−2833.45								
		(−1.36)								
Δ ILCOV3y				188.43**						
				(2.48)						
Δ ILCOV3y×D_t				−207.22**						
				(−2.21)						
Δ ILCOV5y						88.19**				
						(2.52)				
Δ ILCOV5y×D_t						−90.77**				
						(−2.20)				
Δ ILCOV7y								49.90***		
								(3.22)		
Δ ILCOV7y×D_t								−56.33**		
								(−2.24)		
Δ ILCOV10y										33.68***
										(3.19)
Δ ILCOV10y×D_t										−32.71**
										(−2.22)
N	83	71	83	71	83	71	83	71	83	71
adj. R^2	0.109	0.226	0.103	0.195	0.043	0.079	0.026	0.078	0.047	0.118

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Extreme Portfolio CDS Spreads, CDS Bid-ask Spread Illiquidity and Amihud Bond Illiquidity (**Without DEF**).

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS1y$ denotes changes in aggregate CDS Bid-ask spread (in annual basis points). $\Delta ILCOV1y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with 1 year maturity. ILS denotes the AR(2) residual of stationarized aggregate Amihud measure for the US stock market. ILB is the AR(2) residual of the aggregate Amihud measure for the US corporate bond market. RA denotes the risk aversion in levels for the gamma parameter equal to 2. VRP denotes the level of variance risk premium, which is calculated as the difference between the monthly realized volatility of the S& P500 index return (annualized) and the VIX index for the corresponding month. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	122.59	120.62	150.11*	143.90*	151.28**	145.41*	139.91*	133.94*	108.14*	103.46
	(1.36)	(1.31)	(1.90)	(1.82)	(2.10)	(1.97)	(1.98)	(1.85)	(1.78)	(1.67)
Δ ILBAS1y	35.94***	35.65***								
	(7.41)	(6.60)								
Δ ILBAS1y×D_t	−25.59***	−25.69***								
	(−4.87)	(−4.46)								
Δ ILBAS3y			10.49*	9.14						
			(1.85)	(1.54)						
Δ ILBAS3y×D_t			−2.03	−1.29						
			(−0.33)	(−0.20)						
Δ ILBAS5y					26.60***	25.77***				
					(5.69)	(5.28)				
Δ ILBAS5y×D_t					−17.50***	−17.31***				
					(−3.35)	(−3.21)				
Δ ILBAS7y							28.14***	26.91***		
							(3.56)	(2.91)		
Δ ILBAS7y×D_t							−19.08**	−18.43*		
							(−2.30)	(−1.93)		
Δ ILBAS10y									23.47***	20.96***
									(3.71)	(2.84)
Δ ILBAS10y×D_t									−14.48**	−12.44
									(−2.17)	(−1.62)
ILB	124.63	126.20	183.46	180.41	−67.97	−61.51	195.82	194.43	160.67	158.31
	(1.01)	(1.01)	(0.68)	(0.74)	(−0.37)	(−0.35)	(0.82)	(0.83)	(0.72)	(0.75)
ILB×D_t	−622.22	−738.36	−597.24	−788.97	−254.64	−424.72	−457.45	−618.52	−469.13	−587.86
	(−1.16)	(−1.20)	(−1.22)	(−1.58)	(−0.61)	(−0.99)	(−1.03)	(−1.35)	(−1.27)	(−1.57)
RA	−4.64	−4.56	−5.31*	−5.05	−5.45*	−5.21*	−4.78*	−4.53	−3.36	−3.15
	(−1.31)	(−1.26)	(−1.71)	(−1.63)	(−1.91)	(−1.79)	(−1.71)	(−1.58)	(−1.40)	(−1.28)
RA×D_t	3.18	3.11	3.43*	3.17	3.38*	3.14*	2.71	2.46	1.87	1.66
	(1.43)	(1.34)	(1.69)	(1.49)	(1.95)	(1.71)	(1.61)	(1.39)	(1.25)	(1.07)
VRP	3.07*	3.08*	6.57**	6.74**	4.83**	4.90**	6.06**	6.14**	8.06***	8.29**
	(1.78)	(1.78)	(2.31)	(2.28)	(2.13)	(2.07)	(2.15)	(2.09)	(2.68)	(2.61)
VRP×D_t	4.60	3.46	2.42	−0.89	−0.48	−3.37	−4.13	−7.01	−4.50	−6.79
	(0.29)	(0.21)	(0.21)	(−0.08)	(−0.05)	(−0.34)	(−0.40)	(−0.72)	(−0.57)	(−0.87)
Δ TERM	−0.99	−0.72	13.88	16.44	8.07	8.65	24.49	25.54	−10.62	−8.72
	(−0.04)	(−0.03)	(0.44)	(0.60)	(0.29)	(0.30)	(1.25)	(1.37)	(−0.27)	(−0.24)
Δ TERM×D_t	−45.12	−49.09	−38.68	−49.13	−71.47	−76.57	−90.62	−96.47	−23.25	−28.46
	(−0.39)	(−0.40)	(−0.45)	(−0.55)	(−1.11)	(−1.11)	(−1.61)	(−1.65)	(−0.39)	(−0.49)
Δ DEF		19.92		185.01		44.41		79.94		132.49
		(0.23)		(1.55)		(0.44)		(0.79)		(1.06)
Δ DEF×D_t		73.29		−6.39		109.93		72.34		−19.73
		(0.47)		(−0.04)		(0.90)		(0.61)		(−0.14)
N	71	71	71	71	71	71	71	71	71	71
adj. R^2	0.436	0.418	0.357	0.346	0.282	0.266	0.286	0.271	0.368	0.354

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D5: Extreme Portfolio CDS Spreads, CDS Gamma Illiquidity and Amihud Stock Illiquidity (**Without DEF**).

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS1y$ denotes changes in aggregate CDS Bid-ask spread (in annual basis points). $\Delta ILCOV1y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with 1 year maturity. ILS denotes the AR(2) residual of stationarized aggregate Amihud measure for the US stock market. ILB is the AR(2) residual of the aggregate Amihud measure for the US corporate bond market. RA denotes the risk aversion in levels for the gamma parameter equal to 2. VRP denotes the level of variance risk premium, which is calculated as the difference between the monthly realized volatility of the S& P500 index return (annualized) and the VIX index for the corresponding month. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	43.08	43.58	54.87	52.92	59.55	55.40	46.01	43.95	32.67	31.13
	(0.72)	(0.68)	(1.04)	(0.98)	(1.24)	(1.12)	(1.01)	(0.95)	(0.81)	(0.74)
Δ ILCOV1y	3338.44*	3172.98*								
	(1.77)	(1.70)								
Δ ILCOV1y×D_t	−3373.12*	−3208.83*								
	(−1.77)	(−1.70)								
Δ ILCOV3y			134.06	104.31						
			(1.65)	(1.53)						
Δ ILCOV3y×D_t			−141.48	−111.23						
			(−1.46)	(−1.28)						
Δ ILCOV5y					68.72**	59.18*				
					(2.20)	(1.97)				
Δ ILCOV5y×D_t					−67.26*	−57.10				
					(−1.84)	(−1.59)				
Δ ILCOV7y							38.67***	33.86***		
							(2.98)	(2.94)		
Δ ILCOV7y×D_t							−40.84*	−35.76*		
							(−1.95)	(−1.73)		
Δ ILCOV10y									27.05***	22.53***
									(2.66)	(2.89)
Δ ILCOV10y×D_t									−24.12*	−19.48*
									(−1.83)	(−1.68)
ILS	127.99***	125.65***	127.85***	126.31***	94.79***	95.20***	116.81***	116.21***	116.75***	115.81***
	(3.66)	(3.47)	(4.46)	(4.23)	(3.05)	(2.92)	(3.42)	(3.39)	(3.74)	(3.72)
ILS×D_t	5.87	12.14	−26.26	−33.96	5.45	−17.35	−10.02	−20.61	−22.16	−28.78
	(0.04)	(0.06)	(−0.25)	(−0.29)	(0.06)	(−0.17)	(−0.11)	(−0.18)	(−0.28)	(−0.32)
RA	−1.48	−1.50	−1.59	−1.50	−1.86	−1.66	−1.09	−0.99	−0.43	−0.34
	(−0.63)	(−0.60)	(−0.77)	(−0.71)	(−0.98)	(−0.85)	(−0.61)	(−0.54)	(−0.27)	(−0.21)
RA×D_t	2.07	2.09	1.74	1.64	1.53	1.28	0.92	0.80	0.24	0.14
	(1.07)	(0.97)	(1.11)	(0.95)	(1.07)	(0.84)	(0.66)	(0.55)	(0.20)	(0.11)
VRP	2.90	2.92	4.67*	4.80*	3.33	3.58	4.46	4.65	6.09*	6.31*
	(1.17)	(1.09)	(1.95)	(1.89)	(1.07)	(1.10)	(1.38)	(1.36)	(1.75)	(1.69)
VRP×D_t	18.36	18.58	11.10	10.33	4.03	2.19	2.79	1.86	−1.72	−2.43
	(1.04)	(1.01)	(0.84)	(0.70)	(0.37)	(0.19)	(0.25)	(0.16)	(−0.19)	(−0.26)
Δ TERM	−6.17	−3.66	8.30	11.93	3.31	5.75	17.82	20.26	−13.93	−10.42
	(−0.20)	(−0.13)	(0.26)	(0.43)	(0.14)	(0.27)	(1.10)	(1.36)	(−0.35)	(−0.29)
Δ TERM×D_t	40.56	36.53	9.72	9.47	−5.03	0.15	−22.07	−20.94	40.06	38.98
	(0.32)	(0.35)	(0.09)	(0.10)	(−0.05)	(0.00)	(−0.20)	(−0.20)	(0.38)	(0.39)
Δ DEF		104.87		173.32*		100.70		113.74		168.38*
		(1.06)		(1.78)		(1.11)		(1.31)		(1.83)
Δ DEF×D_t		−119.26		−135.45		−9.43		−69.65		−138.31
		(−0.34)		(−0.56)		(−0.05)		(−0.36)		(−0.84)
N	83	83	83	83	83	83	83	83	83	83
adj. R^2	0.107	0.082	0.100	0.075	0.035	0.011	0.027	0.000	0.072	0.048

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D6: Extreme Portfolio CDS Spreads, CDS Gamma Illiquidity and Amihud Bond Illiquidity (**Without DEF**).

This table reports monthly regressions with changes in portfolio CDS spread (equally weighted) with different maturities as a dependant variable. t-statistics are calculated based on standard errors corrected for autocorrelation and heteroscedasticity (Newey-West). N denotes the number of observations used in the regression analysis. adj. R^2 denotes the adjusted R^2 statistics. $\Delta ILBAS1y$ denotes changes in aggregate CDS Bid-ask spread (in annual basis points). $\Delta ILCOV1y$ denotes changes in aggregate monthly gamma measure of illiquidity for CDS spreads with 1 year maturity. ILS denotes the AR(2) residual of stationarized aggregate Amihud measure for the US stock market. ILB is the AR(2) residual of the aggregate Amihud measure for the US corporate bond market. RA denotes the risk aversion in levels for the gamma parameter equal to 2. VRP denotes the level of variance risk premium, which is calculated as the difference between the monthly realized volatility of the S& P500 index return (annualized) and the VIX index for the corresponding month. $\Delta TERM$ denotes changes in term spread, which is defines as the difference between 10-year constant maturity Treasury bond yields and 3-month constant maturity Treasury bill yields. ΔDEF denotes changes in default spread, which is defines as the differences between Moody's Aaa and Baa bond yields.

	1y		3y		5y		7y		10y	
	without	with	without	with	without	with	without	with	without	with
Cons	125.93	113.80	114.63	106.14*	116.18*	107.39**	96.17	86.19	78.43	69.72
	(1.40)	(1.42)	(1.52)	(1.69)	(1.88)	(2.06)	(1.57)	(1.65)	(1.51)	(1.52)
Δ ILCOV1y	3018.05	2821.86								
	(1.46)	(1.35)								
Δ ILCOV1y×D_t	−3031.59	−2833.45								
	(−1.47)	(−1.36)								
Δ ILCOV3y			220.63**	188.43**						
			(2.40)	(2.48)						
Δ ILCOV3y×D_t			−241.26**	−207.22**						
			(−2.28)	(−2.21)						
Δ ILCOV5y					96.92***	88.19**				
					(2.80)	(2.52)				
Δ ILCOV5y×D_t					−100.00**	−90.77**				
					(−2.47)	(−2.20)				
Δ ILCOV7y							55.06***	49.90***		
							(3.57)	(3.22)		
Δ ILCOV7y×D_t							−61.07**	−56.33**		
							(−2.47)	(−2.24)		
Δ ILCOV10y									38.50***	33.68***
									(3.22)	(3.19)
Δ ILCOV10y×D_t									−37.32**	−32.71**
									(−2.40)	(−2.22)
ILB	219.78	225.67	114.94	122.12	57.01	63.64	63.23	72.64	49.30	61.33
	(1.22)	(1.42)	(0.44)	(0.52)	(0.23)	(0.28)	(0.30)	(0.37)	(0.20)	(0.28)
ILB×D_t	−1486.84***	−1973.55***	−1057.65*	−1419.82**	−725.21	−1088.28*	−758.84	−1128.21*	−660.19	−983.08*
	(−2.92)	(−3.61)	(−1.80)	(−2.36)	(−1.21)	(−1.75)	(−1.35)	(−1.86)	(−1.37)	(−1.92)
RA	−4.56	−4.09	−3.86	−3.51	−4.10*	−3.72*	−3.03	−2.62	−2.19	−1.82
	(−1.31)	(−1.32)	(−1.34)	(−1.47)	(−1.72)	(−1.83)	(−1.29)	(−1.29)	(−1.09)	(−1.02)
RA×D_t	5.05**	4.24*	4.13**	3.48*	3.56**	2.90*	2.84*	2.22	1.92	1.36
	(2.29)	(1.81)	(2.10)	(1.78)	(2.12)	(1.70)	(1.72)	(1.34)	(1.39)	(0.98)
VRP	6.42**	6.32**	7.43***	7.50***	4.91	5.12	6.73*	6.88*	8.43**	8.60**
	(2.52)	(2.30)	(2.79)	(2.71)	(1.52)	(1.53)	(1.88)	(1.86)	(2.26)	(2.22)
VRP×D_t	35.24**	21.98	27.30*	16.60	16.91	6.37	15.94	6.40	8.86	0.48
	(2.10)	(1.39)	(1.77)	(1.08)	(1.25)	(0.51)	(1.16)	(0.50)	(0.91)	(0.05)
Δ TERM	−11.72	−9.33	4.80	8.08	0.84	2.66	15.50	17.38	−15.56	−12.68
	(−0.36)	(−0.30)	(0.15)	(0.29)	(0.03)	(0.10)	(0.76)	(0.90)	(−0.39)	(−0.35)
Δ TERM×D_t	33.21	−4.28	10.73	−17.96	18.48	−9.76	4.79	−23.33	64.93	39.41
	(0.28)	(−0.04)	(0.11)	(−0.21)	(0.21)	(−0.13)	(0.05)	(−0.28)	(0.70)	(0.50)
Δ DEF		128.83		179.94		92.94		117.24		171.90
		(1.06)		(1.50)		(0.77)		(1.00)		(1.40)
Δ DEF×D_t		393.05**		215.92		301.04*		265.71		160.14
		(2.04)		(1.10)		(1.82)		(1.42)		(0.96)
N	71	71	71	71	71	71	71	71	71	71
adj. R^2	0.193	0.226	0.167	0.195	0.045	0.079	0.043	0.078	0.084	0.118

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$